Down by the Water: On the Impact of Hydropower on CO_2 Emissions

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Abstract

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1 Introduction

The global economic growth agenda is being met with a desire to rescale the global energy infrastructure. Renewable energy methods are on the rise, primarily including: solar photovoltaic (PV) systems, wind turbines and hydroelectric power (HEP), with the goal of lowering society's impact on the depletion of earth's natural resources and contribution to the greenhouse effect by burning fossil fuels.

Studies show that carbon dioxide, CO_2, emissions are the primary cause of global warming. Together with the other greenhouse gases (GHGs) methane, CH_4, and nitrous oxide, N_2O, these gases are believed to be causing the climate change phenomena. Here, CO_2 has been the main contributor, accounting for 74.4% of the GHGs, CH_4 and N_2O account for roughly 17.3% and 6.2% respectively (Perone, 2024).

The impacts of climate change are already being felt by society. More extreme weather events, such as hurricanes, floods and wildfires are occurring with increased frequency. This trend creates hazardous situations and causes substantial financial losses. For instance, a study analyzing the economic impact of climate change on the US agricultural sector found that climate change could lead to an average annual loss of $4.5 billion in agricultural profits over the period 2010–2100 (Deschênes and Greenstone, 2012). Expanding to a more global perspective, studies predict that a 1°C rise in temperature could lead to a 12% decrease in global GDP (Bilal and Känzig, 2024). These examples illustrate the far-reaching consequences of climate change, which jeopardize both present systems and the foundations of future economic stability

In addition, climate change also drives human displacement due to altered weather patterns. Prolonged droughts in equatorial regions are a major factor as it forces millions to leave their homes. By 2050, projections suggest that up to 216 million people could be displaced within their countries across six world regions (World Bank, 2021). Poorer regions, which are often located in areas most affected by climate change and lack the resources to adapt, are disproportionately impacted. In contrast, wealthier nations are better protected due to their financial and technological capacities. This inequality demonstrates another need for urgent action. Therefore, it is crucial to explore how the global energy infrastructure can be reshaped in order to mitigate the effects of climate change and promote a more sustainable future.

Several studies have shown that a 1% increase in the aggregated production/consumption of nonrenewable fossil fuels causes a 0.68% - 1% increase in carbon emissions (Perone, 2024). PASTE NEW TEXT. THEN BRIEFLY EXPLAIN WHAT WILL BE DONE

Hence, for humanity to steer away from a potential catastrophe, or like Bill Nye called it the *"sixth mass extinction event"*, there is a need to steer away from fossil fuels.

Nomenclature

ADF Augemented Dickey Fuller
AGM Augmented Mean Group
AIC Akaike Information Criterion
ARDL Autoregressive Distributed Lag Model
BIC Bayesian Information Criterion
CADF Cross-sectional ADF
CD Cross-sectional Dependence
CH_4 Methane
CO_2 Carbon Dioxide
DF Dickey-Fuller
DFE Dynamic Fixed Effects
EG Engle-Granger
EKC Environmental Kuznets Curve
FMOLS Fully Modified OLS
GHG Green House Gas
HAC Heteroskedasticity and Autocorrelation Consistent
HEP Hydroelectric Power
KPSS Kwiatkowski–Phillips–Schmidt–Shin
KT Karavias and Tzavalis
MG Mean Group
N_2O Nitrous Oxide
OLS Ordinary Least Squares
PMG Pooled Mean Group
PO Phillips-Ouliaris
PP Phillip Perron
PVAR Panel Vector Autoregression
STIRPAT Stochastic Impacts by Regression on Population, Affluence and Technology
VECM Vector Error Correction Model
ZA Zivot-Andrews

This report will focus on the impacts of hydropower on CO_2 emissions as a renewable alternative to fossil fuels.

the dynamic relationship between hydropower consumption and CO2 emissions

In the next section, state-of-the-art academic literature related to this topic will be reviewed. In the subsequent sections, an econometric analysis is performed on the data to investigate a possible causal relationship between the use of Hydropower and its impact on carbon emissions. At last, a conclusion is presented displaying the findings of this research.

2 Academic Research Findings

A substantial amount of research has been conducted on the relationship between the disaggregated use of hydroelectric power and CO_2 emissions. The majority of these studies focuses on the substitution of hydroelectric power for traditional fossil fuels and the corresponding impact it has on CO_2 emissions, using traditional econometric methodologies such as ARDL and VECM. Here, some studies also account for cross-sectional dependence in panel data by utilizing methods like the augmented mean group (AGM).

The first analyzed paper, Perone (2024), starts by analyzing the aggregated energy mix and then splitting up the mix to analyze the disaggregated effects of an energy source on the CO_2 emissions using panel data. The analysis starts with extensive testing of data properties, testing for cross-sectional dependence in the panel dataset by means of the CD test and performing CADF (cross-sectional Augmented Dickey Fuller, and a KT test for sensitivity) unit-root tests on the panel data before the statistical modeling starts. Then the paper continues by assessing the heteroskedasticity within the large panel by using the heteroskedasticity and autocorrelation consistent (HAC) robust version of a Delta test, Δ. After performing these tests, a panel ARDL model with DFE, MG and PMG (dynamic fixed effects, mean group and pooled mean group, respectively) is used together with a PVAR (Panel Vector Autoregression) model in a Granger Causality framework to find causal relationships between the disaggregated renewable energy groups and CO_2 emissions.

Perone (2024) concludes that for 27 OECD countries hydroelectric power is the second greatest, behind geothermal and bio-fuels, alternative to fossil fuels for the reduction of CO_2 emissions. It finds a highly statistically significant negative unidirectional relationship of hydropower on CO_2 emissions: a one-unit TWh increase in hydropower results in a 0.09 metric tons decrease in CO_2 emissions per capita.

Al-Mulali et al. (2015) used FMOLS in a VECM framework to establish the relationship between economic growth in terms of GDP and a subsequent increase in CO_2 emissions for 23 European countries. The paper then addresses that, by use of Granger causality, combustible renewable and waste generation, hydroelectric and nuclear power have a negative causal relationship with CO_2 emission.

Bilgili et al. (2021) utilizes a wavelet methodology to assess the impact of hydropower on CO_2 emissions. The paper concludes that the impacts in the short-run (1-4 years) and in the long-run (4-8 years) are different. In the short-run, the outcome states that utilizing hydroelectric power intensifies the CO_2 emissions in the USA. As possibility, the paper points towards short-run technological features, market structure and financial constraints. In the long-run, hydroelectric power becomes a clean energy, effectively reducing the overall CO_2 emissions.

Bello et al. (2018) looks at the impact of hydroelectric power on environmental degradation by analyzing its impact on four variables: ecological footprint, carbon footprint, water footprint and CO_2 emissions in Malaysia. The latter is treated as the target variable. For this, the STIRPAT model in combination with EKC hypothesis tests is used to assess this relationship. Perron unit root (Perron, 1997) test are employed to ensure that the data do not exhibit $I(2)$ or higher behavior, required by the ARDL bounds testing approach for cointegration. To identify the direction of the long-run relation, Granger causality in a VECM framework are deployed. Sensitivity tests of the results are performed by controlling for the fossil fuels in each equation.

Bello et al. (2018) concludes that there is a significant negative unidirectional relationship between the consumption of hydroelectric power and CO_2 emissions, established by the VECM Granger causality framework.

Cai et al. (2018) analyzes the potential cointegration and causalities between CO_2 emissions, clean energy usage and economic growth (in terms of GDP growth). The paper describes how ADF, KPSS and PP unit root tests are used to identify the order of integration of the data and ensure series are at least $I(1)$ for the subsequent ARDL analysis. In addition, to assess the stationarity of the data under structural breaks, a GLS unit root test is used. The paper describes a bootstrap ARDL model to test for cointegration among variables. Subsequently, Granger causality test based on the bootstrap ARDL model.
The paper concludes that the levels of clean energy consumption granger causes GDP growth for Canada, Germany and the US. There is a bidirectional relationship between levels of clean energy consumed and the levels of CO_2 emissions in Germany and unidirectional causal relationship between levels of clean energy consumed and CO_2 emissions in the US.

Overall, the literature shows the methodology framework for the causal relation research between a clean energy source (primarily hydroelectric power) and CO_2 emissions.

First the stationarity of the time series are analyzed using sophisticated methods for structural breaks (PP, (Cai et al., 2018)) or for panel data (CADF, (Perone, 2024)). For panel data, CD tests are employed to assess cross-sectional dependence between variables in the panel, (Perone, 2024). ARDL models are widely used to test for cointegration between variables, (Perone, 2024), (Bilgili et al., 2021), (Bello et al., 2018) and (Cai et al., 2018).

In addition, VECM models are used to assess the Granger causality between variables, (Bello et al., 2018), (Al-Mulali et al., 2015).

For panels, a PVAR model is used to assess the Granger causality between variables, (Perone, 2024).

Then there are also other novel approaches to assess the difference between short- and long-run dynamics of variables, assesed using wavelet methodology, (Bilgili et al., 2021).

Most of the literature finds a significant unidirectional causal relationship between the use of hydroelectric power and CO_2 emissions, (Perone, 2024), (Al-Mulali et al., 2015), (Bello et al., 2018). Or long-run negative correlation between the use of HEP and CO_2 emissions, (Bilgili et al., 2021). Conversely, some literature do not find significant relationships between the use of clean energy sources and CO_2 emissions, (Cai et al., 2018).

2.1 Research Gap

This study will center around the research of the causal relationship between HEP and CO_2 emissions in France and Germany over a period ranging from 1965 to 2020. Where most of the literature addresses the clean energy variable as an aggregate of different sources, this research will focus on the disaggregated hydroelectric energy source and its potential causal relationship with CO_2 emissions using a panel data approach.

The research will use a small panel data set ($N = 2$, Germany and France), while accounting for cross-sectional dependence and structural breaks. Where a lot of studies just show the order of integration for the variables without checking for cross-sectional dependence and structural breaks in the data.

Also, multiple explanatory variables are considered within the panel model: cattle density (cattle per square km), population density, fertilizer use and the percentage of land used for agriculture. Table 1 shows a summary of the literature research described.

3 Graphical Analysis

The dataset analyzed is made available by Perone (Perone, 2024), which investigates the dynamic relationship between renewable energy production and carbon dioxide emissions. The focus of this section is to analyze the CO_2 emissions of France and Germany, together with several explanatory variables from 1965 to 2020 in a graphical way. These variables include population density, agricultural land use as a percentage of the total land area in the country, the number of cattle per square kilometer, the average electricity consumption per capita (kWh), fertilizer use in kilograms per capita and hydropower generation in terawatt hours (TWh), which could collectively influence emission trends. A detailed description and extensive discussion of the variables are available in Perone (2024) and are beyond the scope of this paper.

This section offers an exploratory graphical analysis of the dataset, serving as an initial step toward the econometric methodologies applied in subsequent sections.

Table 1: Summary of literature review.

The literature review

Author(s)	Country	Period	Methodology	Conclusion (HEP)
Perone (2024)	27 OECD countries	1970-2020	CD-test, CADF (KT) tests, Panel ARDL, PVAR Granger causality	Hydropower has a statistically significant negative unidirectional causal relationship with CO_2 emissions.
Al-Mulali et al. (2015)	23 EU Countries	1990-2013	FMOLS and VECM, Granger causality	Hydropower has a negative causal relationship with CO_2 emissions.
Bilgili et al. (2021)	USA	1990-2017	Partial wavelet coherence estimation	Positive correlation between HEP and CO_2 in the short-run. Negative correlation in the long-run.
Bello et al. (2018)	Malaysia	1971-2016	STIRPAT model, Perron unit root test, ARDL and VECM Granger causality	Unidirectional negative causal impact in the long-run dynamics of HEP and CO_2 emissions.
Cai et al. (2018)	G-7 Countries	1965-2015	ADF, KPSS, PP unit root tests, bootstrap ARDL and Granger causality	Mixed results for countries. Bidirectional relationship CO_2 emissions and clean energy usage in Germany. Unidirectional relationship clean energy usage and CO_2 emissions US.

3.1 Summary statistics

The summary statistics in Tables 2 and 3 reveal notable differences between France and Germany. Germany records significantly higher CO_2 emissions, with a mean of 11.81 metric tons per capita, compared to France's 7.26. Similarly, the population density in Germany is substantially higher, averaging 229.51 people per square kilometer, more than double that of France 107.89. In contrast, France allocates a larger proportion of its total land area to agriculture. However, Germany surpasses France in cattle density, reflecting differences in livestock farming practices.

Electric power consumption per capita shows comparable averages in both countries. In particular, France has a higher average use of fertilizers, at 95.72 kilograms per capita, compared to Germany 56.14, suggesting more intensive agricultural practices in France. Additionally, hydropower generation is markedly higher in France, nearly three times Germany's output, highlighting significant differences on their reliance on renewable energy sources.

Table 2: Summary statistics of the explanatory variables in France.

Statistic	Emission	Pop density	Agri	Cattle	kWh	Fertilizer	Hydropower
Count	56.00	56.00	56.00	56.00	56.00	56.00	56.00
Mean	7.26	107.89	55.99	38.51	5641.72	95.72	60.99
Std Dev	1.53	9.51	2.86	3.22	1867.60	24.52	8.86
Min	4.24	90.98	52.15	32.49	1988.34	59.34	45.38
25%	6.55	100.19	53.48	36.00	4136.20	72.46	55.14
50%	6.94	107.71	55.40	37.71	6464.39	98.95	61.45
75%	8.18	116.37	58.17	40.36	7226.64	118.98	66.90
Max	10.34	123.06	62.09	43.97	7734.73	131.60	78.79

3.2 Graphical Analysis

The time series for CO_2 emissions in Germany and France, shown in Figure 1, shows consistently higher emissions for Germany, with a peak in the late 1970s. Followed by a gradual decline in the coming decades. Likewise, France followed a similar pattern, with peaking CO_2 emissions in the late 1970s and a steady down-

Table 3: Summary statistics of the explanatory variables in Germany

Statistic	Emission	Pop density	Agri	Cattle	kWh	Fertilizer	Hydropower
Count	56.00	56.00	56.00	56.00	56.00	56.00	56.00
Mean	11.81	229.51	50.87	47.94	5981.68	56.14	18.66
Std Dev	1.59	5.98	2.70	9.84	1398.10	17.65	2.33
Min	7.69	217.58	47.50	32.35	2194.21	32.32	13.21
25%	10.60	223.89	48.58	37.18	5733.28	40.42	17.42
50%	11.98	230.53	49.67	47.75	6492.31	46.97	18.53
75%	13.21	235.32	53.30	57.34	6913.09	75.54	20.10
Max	14.25	238.02	55.95	61.68	7281.27	80.85	23.12

ward trend since. The persistent trend in both time series suggest non-stationarity, likely to be integrated of order one, $I(1)$, these trends could be removed through differencing or detrending.

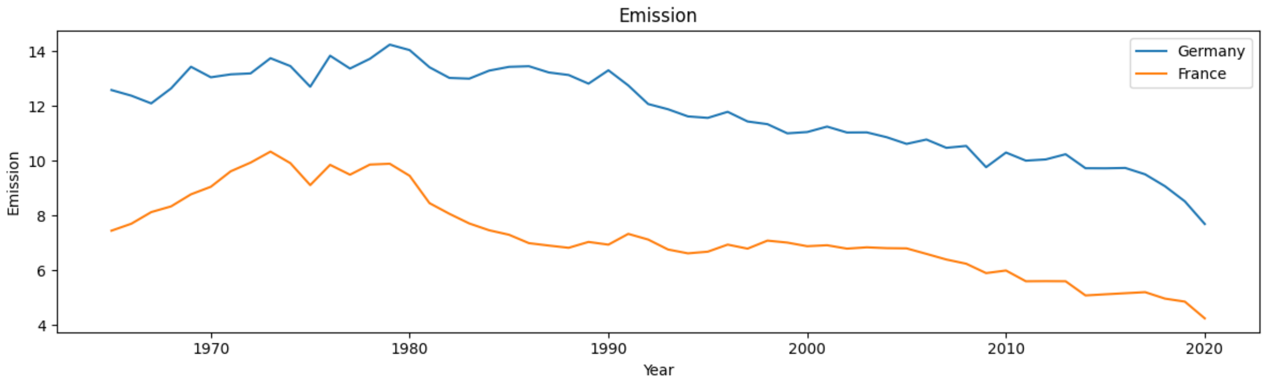

Figure 1: CO_2 emissions in France and Germany, from 1965 to 2020.

The analysis of the explanatory variables in Figure 2 reveals differences in stationarity and the presence of deterministic components. Initially, there is little evidence to support covariance stationarity, as most variables exhibit persistent trends over time. For example, population density shows a clear upward trend in Germany and France. These trends suggest that the population density series are non-stationary and integrated of at least order $I(1)$ and have to be differenced in order to become stationary. Similarly, agricultural land used for farming displays a persistent decline over the decades, reflecting a deterministic component in the series. Likewise, the series has to be differenced in order to become $I(1)$.

Cattle density follows a declining trend in both countries, with Germany initially exhibiting significantly higher levels but experiencing a steep reduction since the late 1970s, likely due to policy changes. Both cattle density series exhibit trends, and Germany shows evidence of a structural break, indicating that both series are probably integrated of at least order $I(1)$.

Similarly, fertilizer use displays non-stationarity, trends, and signs of structural breaks, suggesting that the series is also integrated of at least $I(1)$.

In contrast, electric power consumption per capita shows a clear upward trend over time, stabilizing around 1990. The German series demonstrates visual evidence of a structural break in the late 1980s, likely reflecting policy changes.

These trends and the presence of a structural break support the hypothesis that both electric power consumption series are non-stationary and likely integrated of order $I(1)$, based on a graphical analysis of the data. Formal testing for non-stationarity and structural breaks will be conducted.

Lastly, the hydropower time series for both countries show indications of stationarity. The values appear to fluctuate around a stable mean, suggesting that the series is $I(0)$ and does not require differencing. This characteristic makes hydropower unique compared to the other variables analyzed.

In terms of transformations, Figure **??** in the Appendix shows that logarithmic transformations do not reveal additional patterns or significantly affect the visual characteristics of the series.

Logarithmic transformations are typically beneficial for variables with exponential growth or high variance. However, in this case, the data do not exhibit such properties. Therefore, applying log-transformations would be unnecessary. Instead, formal tests for unit-roots and structural breaks is the most appropriate next step in the econometric analysis.

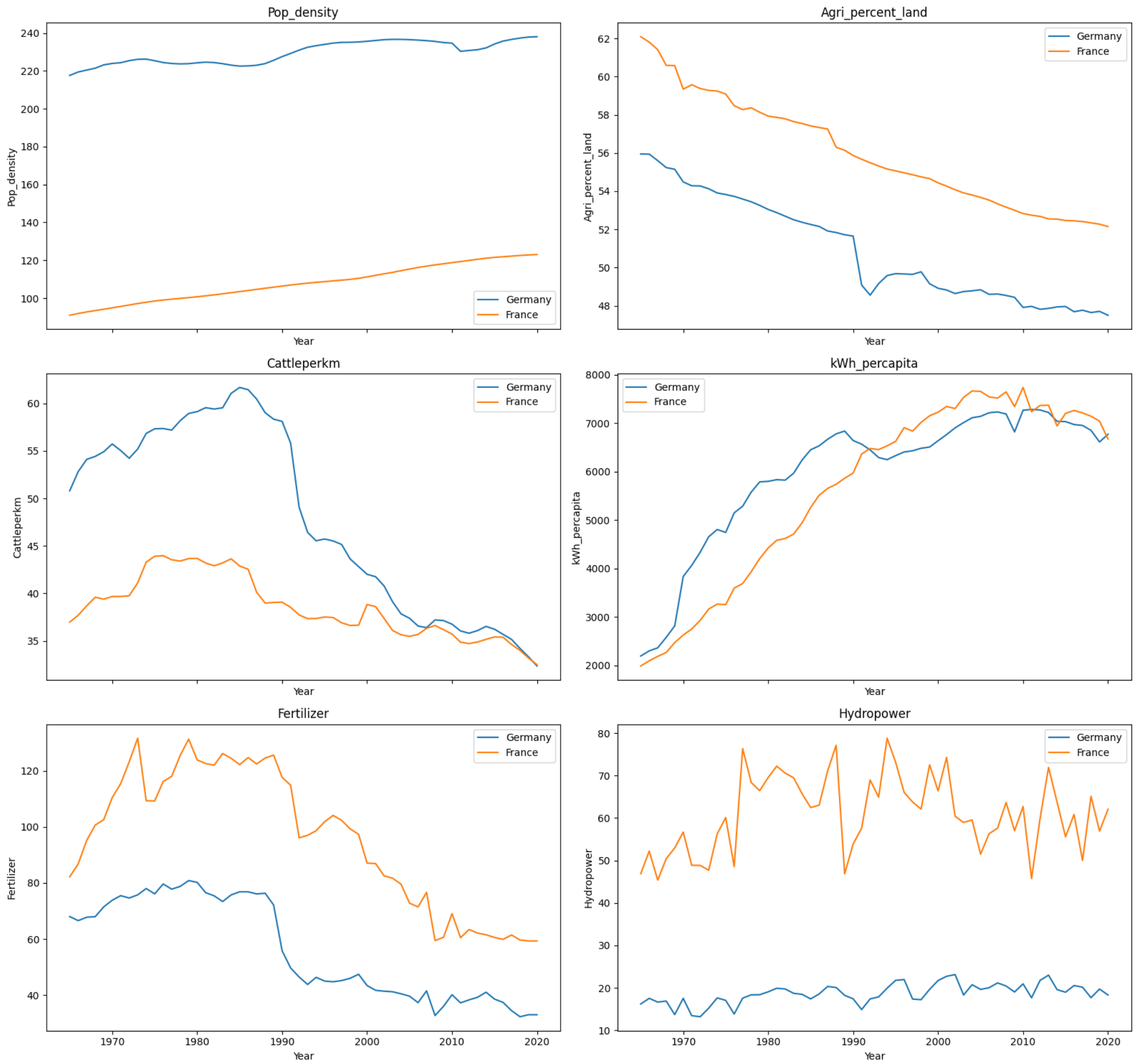

Figure 2: Explanatory variables of the dataset in France and Germany, from 1965 to 2020.

4 Order of Integration

Following the graphical analysis, a more statistical approach to determining the order of integration is presented. Establishing the integration order is essential to identify the properties of the data that are required for econometric modeling. A wide range of unit root tests are applied, including DF, ADF, PP, KPSS, and ZA, to assess the stationarity condition under various hypotheses. The findings of these tests will serve as a basis for selecting the appropriate methods for the cointegration analysis in the subsequent sections.

4.1 Unit Root Tests

A stationary time series is characterized by having finite second order moments (constant mean, variance, and auto-covariance) over time. Non-stationary time series usually exhibit time-varying second order moments (drifting mean, time-varying variance and auto-covariance). Hence, testing for stationarity is essential for justifying the use of certain econometric methods.

As described in the literature, unit root tests are employed for this, testing for the following hypotheses:

$$\begin{cases} H_0 : \text{The time-series data contains a unit root.} \\ H_a : \text{The time-series data is stationary.} \end{cases} \tag{1}$$

Compared to the graphical analysis in the previous section, unit root testing serves as a formal way of inferring the stationarity condition of the time series data and in turn determine the order of integration $I(i)$. Here i refers to the number of times a series has to be differenced in order to become stationary.

Table 4: Summary of Unit Root Tests and Their Features

Test	Null Hypothesis	Accounts for		Remarks
		Autocorrelation	Structural Breaks	
DF	$H_0 : \rho = 1$ (unit root)	No	No	Simple unit root test
ADF	$H_0 : \rho = 1$ (unit root)	Yes	No	Robust test
PP	$H_0 : \rho = 1$ (unit root)	Yes	No	Corrects for heteroskedasticity
KPSS	H_0: The series is stationary ($\rho < 1$)	Yes	No	Tests stationarity
ZA	$H_0 : \rho = 1$ (unit root, with structural breaks)	Yes	Yes	Detects structural breaks

Table 4 displays a summary of the different unit root tests. The tests are applied sequentially, each test adjusting for different properties of the data. The Dickey-Fuller (DF) test of Dickey and Fuller (Dickey and Fuller, 1979) serves as the simplest approach to testing stationarity under the null hypothesis of a unit root. Equation 2 describes an autoregressive process of order one, AR(1).

$$x_t = \lambda x_{t-1} + u_t, \tag{2}$$

Where x_t is the observed time series, γ is the autoregressive parameter and u_t the errorm term, assumed to be white noise. The presence of a unit root is tested under hypothesis 5. Rewriting the AR(1) model in first-difference form makes the test applicable. Here, $\Delta x_t = x_t - x_{t-1}$ and $\gamma = \lambda - 1$.

$$\Delta x_t = \gamma x_{t-1} + u_t, \tag{3}$$

Equation 4 describes the t-test test statistic based on an OLS estimate of γ. Here $\hat{\gamma}$ is the estimated coefficient and $SE(\hat{\gamma})$ is the standard error. Under the null hypothesis, the test statistic follow a non-standard distribution, the Dickey-Fuller distribution.

$$t_\gamma = \frac{\hat{\gamma}}{\text{SE}(\hat{\gamma})}, \tag{4}$$

Instead, the presence of a unit root makes the test dependent on the Dickey-Fuller distribution (Dickey and Fuller, 1979). In addition to the distribution, the estimator for γ exhibits superconsistency under the null and is consistent under the alternative. Therefore, the test is consistent as T goes to infinity REF (slides).

$$\begin{cases} H_0 : t_\lambda = O_p(T^{-1}) \\ H_a : t_\lambda = O_p(\sqrt{T}). \end{cases} \tag{5}$$

However, the DF test assumes no autocorrelation or structural breaks, which could result in biased results. Therefore, the Augmented-Dickey-Fuller (ADF) test extends the DF framework by including lagged values to address serialcorrelation (Dickey and Fuller, 1981). By including lagged differences of x_t and transforming the model into an AR(p), as proposed in Equation 6, the test tries to ensure that the residuals are serially uncorrelated. The null hypothesis remains the same.

$$\Delta x_t = \gamma x_{t-1} + \sum_{j=1}^{k} \beta_j \Delta x_{t-j} + u_t, \tag{6}$$

However, the test is sensitive to the choice of k. An appropriate information criterion is applied to select the lag length. If k is chosen appropriately, the residuals can be assumed to be serially uncorrelated. This ensure that the test statistic will have the same asymptotic distribution as in the serially uncorrelated case REF. One must note, that the inclusion of deterministc components does not change the consistency of the estimator. However, including deterministic components such as an intercept or linear trend does change the assympotic distribtuions. These distributions are documented and estimated by Dickey and Fuller.

The Phillips-Perron (PP) test improves on the ADF test by addressing both serial correlation and heteroskedasticity in the error term (Phillips and Perron, 1988). Unlike the ADF test, which uses parametric adjustments with lagged differences, the PP test applies nonparametric corrections by adjusting the standard errors and test statistic using long-run variance estimates. This makes the PP test less sensitive to the choice of lag length k. While the null hypothesis $H0 : \gamma = 1$ remains consistent with the DF and ADF tests, the key difference lies in its nonparametric approach, allowing for results under less restrictive assumptions.

he Zivot-Andrews (ZA) test determines whether a time series has a unit root while accounting for a single structural break (Zivot and Andrews, 2002). Unlike the previous mentioned tests, it identifies the breakpoint within the data rather than requiring it to be specified in advance. The test considers breaks in the intercept, the trend, or both. The null hypothesis assumes a unit root with no structural break, while the alternative allows for stationarity with a single break. However, a key limitation of the ZA test is that it handles one structural break, which may become problematic when multiple breaks are present in the series.

Lastly, the Kwiatkowski–Phillips–Schmidt–Shin test (Kwiatkowski et al., 1992) test takes a different approach by reversing the hypothesis, as seen in Hypothesis 7, and this test serves as a complementary test to the previous results from the DF, ADF and PP tests as it offers insights into stationarity by testing from a different perspective. The following sections present and discuss the results obtained by applying the unit root tests.

$$\begin{cases} H_0 : \text{The time-series data is stationary.} \\ H_a : \text{The time-series data contains a unit root.} \end{cases} \tag{7}$$

4.2 Unit Root Test Results

This section presents the results of unit root tests for the variables discussed previously for France and Germany, guided by the literature. The results identify the order of integration for each time series, an initial step for cointegration modeling. The test results are presented, followed by a summary and discussion.

Table 5: DF Test Results for Germany

Variable	No constant + No Trend			Constant			Constant + Trend		
	T-stat	p-value	I(i)	T-stat	p-value	I(i)	T-stat	p-value	I(i)
Emission	-1.5722	0.1091	1	1.3104	0.9967	1	-1.9902	0.6067	1
Pop Density	1.1746	0.9377	1	-1.1774	0.6833	1	-2.2707	0.4502	1
Agri Percent Land	-2.4787	0.0127	0	-1.5914	0.4879	1	-2.5252	0.3155	1
Cattle per km	-1.3893	0.1533	1	-0.2539	0.9318	1	-2.1489	0.5186	1
kWh per capita	1.2525	0.9459	1	-4.2341	0.0006	0	-2.3622	0.3999	1
Fertilizer	-1.1816	0.2169	1	-0.4117	0.9081	1	-2.4387	0.3592	1
Hydropower	-0.1923	0.6168	1	-2.9729	0.0375	0	-4.1289	0.0057	0

Table 6: DF Test Results for France

Variable	No constant + No Trend			Constant			Constant + Trend		
	T-stat	p-value	I(i)	T-stat	p-value	I(i)	T-stat	p-value	I(i)
Emission	-1.1604	0.2242	1	0.1366	0.9685	1	-2.9951	0.1335	1
Pop Density	0.8685	0.8964	1	-0.6301	0.8640	1	-3.7303	0.0204	0
Agri Percent Land	-5.4635	0.0000	0	-3.4359	0.0098	0	-2.6678	0.2497	1
Cattle per km	-0.7395	0.3960	1	-0.7087	0.8445	1	-3.0132	0.1284	1
kWh per capita	1.9498	0.9888	1	-3.5028	0.0079	0	2.1534	1.0000	1
Fertilizer	-0.6568	0.4308	1	-0.3801	0.9134	1	-3.4026	0.0510	1
Hydropower	-0.1401	0.6358	1	-3.2452	0.0175	0	-3.1787	0.0887	1

The results of the DF test for France and Germany, as presented in Tables 6 and 5, show different order of integration between variables. The tables presents the results under three specifications, without a constant or trend, with a constant, and with a constant and trend. For Germany, most variables fail to reject the null hypothesis of a unit root at levels. However, most processes become stationary at the first difference, implying that the series are integrated of order 1 (I(1)). kWh per capita and hydropower, on the other hand, have significant p-values, i.e. smaller than $p - value < 0.05$, and a large negative t-statistic, implying stationarity at levels with including a constant. For kWh per capita, the impact of including a trend is evident. The inclusion of a trend changes the result, indicating that the series is integrated of order 1 instead of being stationary at levels. Notably, under including no deterministic component, AGRI rejects the null hypothesis, suggesting stationarity at levels.

For France, the findings indicate that Emission, Cattle per km, and Fertilizer are integrated of order 1 under all specifications, indicating the presence of a unit root. While Population Density is I(1) under the specifications with no deterministic components and with a constant, it becomes stationary when including a trend I(0). On the other hand, Agri Percent Land shows contrasting behavior to Population Density: it has evidence of a unit root when including a trend but is stationary at levels with no deterministic component and with a constant. Lastly, both kWh per capita and Hydropower are stationary when including a constant but are integrated of order 1 when including no deterministic component or a trend.

Table 7: ADF Test Results for Germany

Variable	No constant + No Trend				Constant				Constant + Trend			
	T-stat	p-value	Lags	I(i)	T-stat	p-value	Lags	I(i)	T-stat	p-value	Lags	I(i)
Emission	-1.5143	0.1219	0	1	0.9002	0.9931	0	3	-1.9393	0.6341	0	1
Pop Density	1.1746	0.9377	1	1	-1.3290	0.6158	2	1	-2.8680	0.1731	2	1
Agri Percent Land	-2.9854	0.0028	0	1	-1.5016	0.5327	0	1	-2.5252	0.3155	1	1
Cattle per km	-1.5069	0.1236	2	1	0.1021	0.9662	2	2	-2.1489	0.5186	1	1
kWh per capita	2.0169	0.9907	0	1	-4.5446	0.0002	0	0	-1.9315	0.6382	0	1
Fertilizer	-1.4261	0.1435	0	1	-0.2261	0.9353	0	1	-2.4387	0.3592	1	1
Hydropower	0.4073	0.8027	5	1	-3.7546	0.0034	0	0	-4.7863	0.0005	0	0

Table 8: ADF Test Results for France

Variable	No constant + No Trend				Constant				Constant + Trend			
	T-stat	p-value	Lags	I(i)	T-stat	p-value	Lags	I(i)	T-stat	p-value	Lags	I(i)
Emission	-2.8533	0.0042	8	0	-1.0725	0.7259	8	1	-3.8568	0.0139	12	0
Pop Density	1.3694	0.9568	2	2	-1.1593	0.6908	2	2	-2.7745	0.2065	7	2
Agri Percent Land	-5.9611	0.0000	0	0	-2.8323	0.0538	0	1	-2.6363	0.2635	0	1
Cattle per km	-1.0679	0.2577	3	1	-0.0199	0.9569	3	1	-4.1270	0.0058	10	0
kWh per capita	-1.3985	0.1508	12	2	-2.6240	0.0881	9	1	2.3428	1.0000	4	1
Fertilizer	-0.5796	0.4632	0	1	-0.4509	0.9012	0	1	-3.2790	0.0698	0	1
Hydropower	0.1065	0.7186	3	1	-4.6806	0.0001	0	0	-4.6449	0.0009	0	0

The results of the ADF test for Germany and France, as shown in Tables 7 and 8, build on the DF framework by including lagged differences of the series to address serial correlation in the residuals. The optimal lag length is determined using the AIC information criterion. The inclusion of more lagged differences provides a better adjustment for testing time series with autocorrelation for unit roots.

For Germany, presented in Table 7, the inclusion of lagged differences shows different results compared to the DF test. The Emission series is integrated of order I(1) under all specifications, consistent with the DF test. However, under the no constant + no trend specification, the ADF test suggests a higher order of integration (I(3)), requiring three differences to achieve stationarity. Differencing a series three times can remove insightful properties of the data, so ought to be performed carefully. The order of integration for Population Density, fertilizer and kWh per capita remains the same across both tests and specifications. Implying, that adjusting for autocorrelation does not influence the test results for these series. As for AGRI, the results differ only under including no deterministic component, where the ADF test indicates that the series does not have a unit root when including no deterministic components compared to the stationary at levels findings for the DF test. The Cattle per km series with a constant has an even higher order of integration as compared to the DF test, by increasing the number of lags from 1 to 2. Lastly, Hydropower remains stationary (I(0)) across specifications with a deterministic component and remains to be integrated of order I(1) when including no deterministic components.

Table 8 presents the ADF test results for France. Fertilizer consistently shows integration of order I(1) across all specifications, with only minor differences in t-statistics and p-values due to lag inclusion. As for emission, by including more lagged differences, the series have sufficient evidence of stationarity under no deterministic component as well as including a constant and trend, highlighting the effect for adjusting for serial correlation.

On the other hand, the population density series shift an order of integration up by including more lagged differences. Under all specifications the series become I(2). The AGRI series findings have sufficient evidence to be integrated of order I(1) when including a constant as compared to the no unit root results when performing the DF test. When including 10 lags in the test with a constant and trend, the cattle per square kilometer has a p-value of 0.0058, strong evidence of no unit root, as compared to a p-value of 0.1284 when only including the first lagged difference in the DF test. Under no deterministic components the energy consumption per capita is stationary when differencing the series two times, as compared to once in the DF test. Lastly, the hydropower series is stationary when there are no lags included in the test while including a constant and a combination of a constant and a trend. Highlighting the difference with the DF test, where the hydropower series was stationary only when including a constant.

Most findings are consistent across tests, with some discrepancies. For example, Population Density and Emission with a constant for Germany show higher orders of integration in the ADF test compared to the DF test. These differences require further examination. To address this, the Phillips-Perron (PP) test is used as a nonparametric approach to unit root testing.

Table 9: Phillips-Perron Test Results for Germany and France

Variable	Germany			France		
	t-stat	p-value	I(i)	t-stat	p-value	I(i)
Emission	1.7257	0.9982	I(1)	-0.1887	0.9399	I(1)
Pop Density	-1.4927	0.5371	I(1)	-1.3545	0.6039	I(2)
AGRI	-1.8669	0.3478	I(1)	-3.8328	0.0026	I(0)
CATTLE	-0.0836	0.9510	I(1)	-0.6558	0.8579	I(1)
kWh	-5.3110	0.0000	I(0)	-2.5878	0.0955	I(1)
Fertilizer	-0.4479	0.9018	I(1)	-0.7425	0.8354	I(1)
Hydropower	-4.0191	0.0013	I(0)	-4.8352	0.0000	I(0)

The results of the Philips-Perron (PP) test for Germany and France, presented in Table 9, provide a non-parametric or nuisance parameter-free approach to unit root testing. Thereby, addressing both serial correlation and heteroskedasticity in the residuals.

For Germany, the findings of most variables are of similar order of integration as compared to the ADF and DF tests. The hydropower time series has consistent results across all tests and has sufficient evidence to be integrated of order I(0), indicating no unit roots and implying stationarity. Emission, Population density, AGRI, Fertilizer Show consistent results across test as well, but for enough evidence to be integrated of order I(1), indicating the presence of a unit root. The cattle per square kilometer as well as kWh per capita, while showing some differences between the DF and ADF tests, the PP test results show that the processes seem to be integrated of order I(1), in line with the most common findings of the other tests under different specifications.

For France, the findings of most variables are of different order of integrations as compared to the ADF and DF tests. The series with evidence for stationarity are Hydropower and AGRI, where Hydropower did have promising evidence of no unit root when performing the ADF test, the AGRI series has only shown sufficient evidence for no unit root when including no deterministic components in the test. Showing that accounting for heteroskedasticity has a great influence on the findings. The PP test findings for emissions are similar to the DF test findings and differ from the ADF test findings, showing that the test is subjective to the sensitivity of the chosen number of lags in the regression. The population density series has evidence for multiple unit roots, implying an order of integration of 2, similar to the ADF test results. CATTLE, kWh and Fertilizer have similar findings across test as well.

Overall, the pp test results confirms the previous findings from the DF and ADf test by accounting for heteroskedasiticy.

Table 10 presents the results of the Zivot-Andrews (ZA) test. The ZA test, as discussed earlier, incorporates the possibility of a structural break, providing information on series that are possible impacted by a break. For Germany, the findings are largely similar to previous findings. Including the possibility of accounting for a possible structural break makes the population density series integrated of order 2 and indicative of multiple unit roots. Findings that were not previously found. The same accounts for AGRI fertilizer, where the ZA test findings show evidence of a stationary time series when accounting for a structural break, due to the low p-value as well as quite large test statistics. For France, the findings are more simi-

Table 10: Zivot-Andrews Test Results for Germany and France

Variable	Germany				France			
	t-stat	p-value	Break Point	I(i)	t-stat	p-value	Break Point	I(i)
Emission	-3.6321	0.5930	0	I(1)	-4.5431	0.1068	7	I(2)
Pop Density	-4.0677	0.3110	2	I(2)	-4.3179	0.1843	7	I(2)
AGRI	-5.2184	0.0136	1	I(0)	-4.1396	0.2705	0	I(1)
CATTLE	-4.3254	0.1811	1	I(1)	NaN	NaN	10	I(1)
kWh	-2.2790	0.9921	0	I(1)	0.5989	0.9990	4	I(1)
Fertilizer	-6.6239	0.0002	0	I(0)	-4.0204	0.3398	0	I(1)
Hydropower	-5.5983	0.0029	0	I(0)	-7.1859	0.0000	0	I(0)

lar to the previous tests. Where, Hydropower remains consistently stationary across all tests, and thus not indicative of a unit root in the series. The population density remains integrated of order 2. Notably, the large negative test statistic and significant p-value of AGRI seems to be indicative of no unit root in the series when accounting for a structural break. The remaining variables seem to have somewhat consistent results across tests with some differences when including no or certain deterministic components.

4.3 Order of Integration Discussion

A summary of the unit roots tests are shown in Table 11. The Table highlights the differences in the order of integration across variables for Germany and France for different tests. The findings also show the sensitivity of the different tests on the different properties of the series over time.

Table 11: Summary of Unit Root Test Results

Variable	Germany									France								
	DF			ADF			PP	ZA	Final	DF			ADF			PP	ZA	Final
	n	c	c + t	n	c	c + t				n	c	c + t	n	c	c + t			
Emission	1	1	1	1	3	1	1	1	I(1)	1	1	1	0	1	0	1	2	I(1)
Pop Density	1	1	1	1	1	1	1	2	I(1)	1	1	0	2	2	2	2	2	I(2)
AGRI	0	1	1	1	1	1	1	0	I(1)	0	0	1	0	1	1	0	1	I(1)
CATTLE	1	1	1	1	2	1	1	1	I(1)	1	1	1	1	1	0	1	1	I(1)
kWh	1	0	1	1	0	1	0	1	I(1)	1	0	1	2	1	1	1	1	I(1)
Fertilizer	1	1	1	1	1	1	1	0	I(1)	1	1	1	1	1	1	1	1	I(1)
Hydropower	1	0	0	1	0	0	0	0	I(0)	1	0	1	1	0	0	0	0	I(0)

As a final measure, the most common result across tests (the mode) is used to determine the final order of integration for each variable. Most variables for both Germany and France are found to be integrated of order 1 (I(1)), while Hydropower stands out as stationary at levels (I(0)) for both countries. For Population Density, the German series is consistently identified as I(1), except in the ZA test, which shows sensitivity to accounting for structural breaks. In France, however, Population Density is found to have multiple unit roots, making it integrated of order 2 (I(2)) across most tests. The results show that adding lagged differences and including deterministic components, such as trends, can greatly influence the findings. This highlights the challenges of determining the correct order of integration when series have complex dynamics. By combining results from simple tests like DF, parametric tests like ADF, nonparametric tests like PP, and structural break tests like ZA, a more reliable conclusion can be made. Other tests, such as KPSS, which tests for stationarity instead of a unit root, or extending ZA to handle multiple structural breaks with methods like the Bai-Perron test, could provide further insights for cases with more complex data. However, over-analyzing the order of integration is probably often unnecessary.

5 Cointegration Analysis

5.1 Cointegration Hypotheses

Based on the academic references, discussed in the literature review, a cointegration relationship between hydropower and emissions is expected. Furthermore, hydropower is expected to be further cointegrated with energy consumption (primarily clean energy consumption, which in turn is expected to be cointegrated with the population density. The percentage of land used for agriculture is expected to be cointegrated with the cattle density.

For the cointegration analysis, it is assumed that all time series are integrated of order one, $I(1)$. This section will analyze the cointegration relationships between variables using the: Engle-Granger (EG) cointegration method (Engle and Granger, 1987), the Phillips-Ouliaris (PO) cointegration method (Phillips and Ouliaris, 1990) and the Johansen cointegration method (Johansen, 1991).

5.2 Cointegration Methodology

The EG test for cointegration between two time-series by estimating a standard OLS regression of the two series. The idea is that if two time series of $I(1)$ are cointegrated, there exists a linear relationship between these variables:

$$\hat{Y}_t = \hat{\alpha} + \hat{\beta} X_t \tag{8}$$

Here, β denotes the long-run coefficient between the two series. Subsequently, the residuals of the OLS regression, $\hat{\epsilon}_t$ are calculated and a stationarity test, ADF test, is performed to test for stationarity in the OLS residuals:

$$\Delta\hat{\epsilon}_t = \phi\hat{\epsilon}_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta\hat{\epsilon}_{t-i} + u_t \tag{9}$$

Where, $\hat{\epsilon}_t = Y_t - (\hat{\alpha} + \hat{\beta} X_t)$, p denotes the number of lags to take into account, set to the default value of $12 \cdot \left(\frac{n}{100}\right)^{0.25}$, where n denotes the number of observations in the data set. ϕ is the parameter of interest on which a t-test is performed using the ADF critical values.

The PO test is an elaboration on the EG approach to cointegration, accounting for serial correlation and possible endogeneity in the long-run regression (equation 8) residuals, $\hat{\epsilon}_t$. It uses the same initial setup as the EG approach, regressing both $I(1)$ series on eachother (see equation 8) and then checking the stationarity condition with the ADF test (see equation 9).

The PO test, however, differs by calculating a different critical-values and doing four different hypotheses tests on residuals of the ADF regression. It performs a residual-based t-test and computes a test-statistic, Z_t, defined as:

$$\hat{Z}_t = \frac{\hat{\sigma}_u}{\hat{\omega}^2} \cdot \sqrt{T} \cdot z \tag{10}$$

Here, σ_u denotes the short-run variance of the residuals, ω the long-run variance of the residuals and z is a basis function defined as: $z = (\hat{\alpha} - 1) - \frac{\hat{\omega}_1^2}{\hat{\sigma}_u}$. Here, $\hat{\alpha}$ equals the estimated coefficient for the lagged residuals in an ADF regression.

The Z_t test statistic is a robust statistic for both serial correlation and possible endogeneity. For identifying the long-run relationship between two variables, the test makes use of an additional test-statistics, Z_α, defined as:

$$\hat{Z}_\alpha = T \cdot z \tag{11}$$

Thus, for testing the short-run pairwise cointegration of two $I(1)$ time-series, the Z_t test statistic is compared with the PO critical values for the Z_t statistic. For the long-run relationship between two series, the Z_α statistic is compared with its corresponding PO critical value. Table 14 shows the critical values for the PO cointegration test.

The Johansen test is a multivariate method for cointegration analysis in panel data. This method constructs a VAR model for the multivariate panel data:

$$\boldsymbol{X}_t = \boldsymbol{\Phi}_1 \boldsymbol{X}_{t-1} + \boldsymbol{\Phi}_2 \boldsymbol{X}_{t-2} + \cdots + \boldsymbol{\Phi}_p \boldsymbol{X}_{t-p} + \epsilon_t \tag{12}$$

Here, $\boldsymbol{X}_t$ is a $k \times 1$ vector, $\boldsymbol{\Phi}_p$ is a $k \times k$ matrix containing the lagged values of X_t.

Subsequently, the VAR(p) model is rewritten into a VECM model:

$$\Delta\boldsymbol{X}_t = \Pi\boldsymbol{X}_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta\boldsymbol{X}_{t-i} + \epsilon_t \tag{13}$$

The rank of the matrix, Π, determines the cointegration of the multivariate time-series panel:

$$\begin{cases} \text{if } \operatorname{rank}(\Pi) = 0 : \text{no cointegration, series remain } I(1) \\ \text{if } \operatorname{rank}(\Pi) = r : (0 < r < k) : \ r \text{ coint relations} \\ \text{if } \operatorname{rank}(\Pi) = k : \text{all variables stationary} \end{cases}$$

When the rank equals $0 < r < k$, then the matrix can be decomposed into:

$$\Pi = \alpha\beta' \tag{14}$$

Here, α denotes the $k \times r$ adjustment coefficients matrix, β denotes a $k \times r$ matrix holding the cointegration vectors.

The rank of Π is determined by two hypothesis tests using the eigenvalues of Π and compares these with the critical values.

5.3 Cointegration Results

The trend categorization (n, c or ct) for the cointegration analysis are determined on a pairwise basis using information criterion. The ADF regression in equation 9 is adjusted for the three trend types:

$$\begin{cases} \Delta\hat{\epsilon}_t = \text{equation } 9 & \text{if trend type is } n \\ \Delta\hat{\epsilon}_t = \hat{\alpha} + \text{equation } 9 & \text{if trend type is } c \\ \Delta\hat{\epsilon}_t = \hat{\alpha} + \hat{\gamma}t + \text{equation } 9 & \text{if trend type is } ct \end{cases} \tag{15}$$

For each of the pairwise regressions, the AIC and p-values are calculated for the different deterministic components. The lowest scoring regression type on AIC or significant p-value is considered for the relationship between the two time-series. Table 14 show the impact of the different trend types on the critical values for the EG and PO tests.

Subsequently, the EG and PO tests are performed on a pairwise basis to assess the cointegration relations between two time-series. Table 12 shows the pairwise significant cointegration relationships.

Then, the cointegration analysis for the Johansen test is evaluated. The number of estimated cointegration vectors based on the trace statistic determines the cointegration rank of matrix Π. A rank of two and three for Germany and France are estimated, respectively. The beta vectors are used to check the stationarity condition of the systems residuals using the beta vectors with an ADF test.

Using a VECM model, the beta values inside the Γ vector are estimated for the cointegration vectors to identify the long-run equilibrium relations between variables. Table 13 shows the cointegration vector for the Emissions variable for both countries.

Table 12: Significant pairwise cointegration relationships from the EG and PO tests. $\Rightarrow$ indicates a one-way cointegration relation, $\Leftrightarrow$ indicates a bidrectional cointegration relation.
EMS: Emissions, PopD: population density, CONS: consumption kWh, CAT: cattle density, FERT: fertilizer used, APCT: percentage agricultural land.

Variables	Germany			France		
	EG	PO (Z_t)	PO (Z_α)	EG	PO (Z_t)	PO (Z_α)
EMS	$\Rightarrow$ CONS	$\Rightarrow$ CONS	$\Rightarrow$ CONS	$\Leftrightarrow$ HEP		
PopD	$\Leftrightarrow$ CONS	$\Leftrightarrow$ CONS		$\Leftrightarrow$ CONS	$\Rightarrow$ CONS	
	$\Leftrightarrow$ HEP	$\Leftrightarrow$ HEP	$\Leftrightarrow$ HEP	$\Rightarrow$ FERT	$\Rightarrow$ FERT	
CONS	$\Rightarrow$ APCT	$\Rightarrow$ APCT				
	$\Leftrightarrow$ HEP	$\Leftrightarrow$ HEP				
HEP	$\Rightarrow$ EMS	$\Rightarrow$ EMS	$\Rightarrow$ EMS		$\Rightarrow$ EMS	$\Rightarrow$ EMS
	$\Rightarrow$ APCT	$\Rightarrow$ APCT		$\Rightarrow$ APCT	$\Rightarrow$ APCT	$\Rightarrow$ APCT
	$\Rightarrow$ CAT	$\Rightarrow$ CAT		$\Rightarrow$ CAT	$\Rightarrow$ CAT	$\Rightarrow$ CAT
				$\Leftrightarrow$ FERT	$\Leftrightarrow$ FERT	$\Rightarrow$ FERT
APCT				$\Rightarrow$ CAT	$\Rightarrow$ CAT	
				$\Rightarrow$ FERT	$\Rightarrow$ FERT	
				$\Rightarrow$ CONS	$\Rightarrow$ CONS	

Table 13: Johansen cointegration vector coefficients.

Variable	Germany	France
Emissions	1.00	1.00
Pop density	$2.683{\cdot}10^{-17}$	$1.110{\cdot}10^{-16}$
Agri percentage	18.440	0.00
Cattle density	2.166	$8.327{\cdot}10^{-17}$
kWh per capita (CONS)	0.0328	$6.505{\cdot}10^{-18}$
Fertilizer	-3.431	$-2.082{\cdot}10^{-17}$
Hydropower (HEP)	-9.001	-0.0252

From Table 12, it can be hypothesized that, for Germany, the population density has an impact a short run cointegration effect with energy consumption and a bidirectional short- and long-run cointegration relation exists. For France, the short-run cointegration relation with consumption remains, but the HEP is replaced with a unidirectional cointegration relation with fertilizer usage.

What is also notable is the absence of cointegration relations with APCT in Germany where it persists in

France. Which could potentially be explained by the size of the agriculture industry in both countries.

Most interesting is the persistent short- and long-run unidirectional cointegration relation between HEP and emissions, potentially indicating a causal relationship, which is investigated later.

The values from Table 13 are further investigated with formal methods in the next session.

5.4 Analysing the Cointegration Vectors

5.5 Johansen's Analysis

HERE COMES JOHANSEN ANALYSIS

6 Causal Analysis

6.1 Methodology

WE ARE TESTING GRAGNER NON-CAUSALITY!

Granger causality refers to a predictive relationship between two variables, where the past values of one variable improve the prediction of another variable. It is important to emphasize that Granger causality does not imply causation in the traditional sense but rather focuses on the temporal predictive power of one variable over another (Granger, 1969).

The Granger causality test is conducted by fitting a regression model where the dependent variable is regressed on its own past values (lags) as well as the past values of the independent variable. Mathematically, consider two variables, X_t and Y_t. The Granger causality test evaluates the following models:

$$Y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i Y_{t-i} + \sum_{i=1}^{p} \beta_i X_{t-i} + \epsilon_t, \tag{16}$$

$$X_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i X_{t-i} + \sum_{i=1}^{p} \delta_i Y_{t-i} + \eta_t, \tag{17}$$

where p is the number of lags, ϵ_t and η_t are error terms and the coefficients β_i and δ_i determine whether Granger causality exists.

To test whether X_t Granger-causes Y_t, we use the null hypothesis $H_0 : \beta_1 = \beta_2 = \cdots = \beta_p = 0$. If the null is rejected, it indicates that past values of X_t significantly improve the prediction of Y_t. This then implies Granger causality.

The test requires that all variables be stationary ($I(0)$), as non-stationary data can lead to spurious results (Enders, 2014). The stationarity of the data was established in earlier sections through rigorous testing and differencing where necessary.

The number of lags (p) is a critical parameter for the Granger causality test, as it determines the time horizon over which causality is tested. Lag selection in this analysis is guided by model selection criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These criteria balance model fit and complexity, ensuring that the chosen lags capture significant dynamics without overfitting (Lütkepohl, 2005).

Cointegration analysis in Section 5 revealed whether variables share a long-term equilibrium relationship. If cointegration is present, standard Granger causality tests on differenced data will only capture short-term predictive dynamics. This is since the long-term equilibrium adjustment is removed through differencing. Although the Vector Error Correction Model (VECM) is the standard approach for capturing both short- and long-term dynamics, the focus of this section remains on short-term Granger causality. Therefore, any findings here should be interpreted as addressing immediate predictive relationships, while results from cointegration tests display possible complementary long-term effects.

6.2 Granger Causality Test Results

7 Comparison with Perone (2024)

7.1 Unit Root Tests and Order of Integration

The author has used panel tests such as CADF and KT, which are suitable for analyzing stationary processes for 27 OECD countries as a group, accounting for cross-sectional dependence. In contrast, we used tests such as ADF, KPSS, and Zivot-Andrews, focusing only on independent time series for Germany and France. The author addressed structural breaks using the KT test, which identifies structural breaks by considering breaks in both the intercept and trend of panel data over time, while we employed Zivot-Andrews to identify breaks at the country level. Zivot-Andrews identifies breaks by endogenously testing for a single break in either the intercept, trend, or both.

Below is the comparison of our results with the author's:

CO_2 Emissions: The author reported CO_2 emissions as I(1) or I(0). Our results aligned with the author's findings for Germany, as ADF, Phillips-Perron, and Zivot-Andrews tests confirmed I(1). However, KPSS suggested I(0). For France, most tests indicated I(1), consistent with the author's findings. However, Zivot-Andrews suggested I(2) due to a structural break, creating slight ambiguity.

Population Density: The author classified population density as I(1). For Germany, ADF and Phillips-Perron tests supported I(1), while Zivot-Andrews showed I(2) with a structural break, and KPSS suggested I(0). Similarly, for France, ADF and Phillips-Perron results showed I(1), but Zivot-Andrews showed I(2), and KPSS indicated I(0). Overall, many of our findings matched the author's I(1) classification, despite some discrepancies.

Agricultural Land Use: The author reported agricultural land use as I(1). For both Germany and France, ADF and Phillips-Perron tests agreed with the author's findings, identifying it as I(1). However, Zivot-Andrews and KPSS indicated I(0) with structural breaks, suggesting differences in methodology or break-handling approaches.

Cattle Density: The author reported cattle density as I(0) or I(1). For Germany, ADF and Phillips-Perron classified it as I(1), consistent with the Zivot-Andrews test, which found no significant structural break. However, KPSS suggested I(0). For France, most tests, including ADF, Phillips-Perron, and Zivot-Andrews, indicated I(1) with a structural break, while KPSS showed I(0). These mixed results align with the author's findings of ambiguous integration orders.

Energy Use (kWh per capita): The author identified energy use as I(1). For Germany, our results largely aligned with this, as ADF, Phillips-Perron, and Zivot-Andrews showed I(1). However, KPSS suggested I(0). For France, ADF, Phillips-Perron, and Zivot-Andrews similarly showed I(1), while KPSS indicated I(0), creating some inconsistency with the author.

Fertilizer Use: The author reported fertilizer use as I(1). Our results for Germany and France were consistent with this classification, as ADF, Phillips-Perron, and Zivot-Andrews tests confirmed I(1). However, KPSS showed I(0) for both countries, introducing slight discrepancies.

Hydropower: The author classified hydropower as I(0), which aligns perfectly with our results. All the tests, including ADF, Phillips-Perron, Zivot-Andrews, and KPSS, confirmed stationarity (I(0)) for hydropower in both countries, with Zivot-Andrews identifying structural breaks.

Appendices

A Engle-Granger & Phillips-Ouliaris Critical Values

Table 14: Critical values for the pairwise Engle-Granger (Engle and Granger, 1987) and Phillips-Ouliaris (Phillips and Ouliaris, 1990) cointegration tests.

Trend Type	Engle-Granger			Phillips-Ouliaris (Z_t)			Phillips-Ouliaris (Z_α)		
	10%	5%	1%	10%	5%	1%	10%	5%	1%
None (n)	-2.55	-2.88	-3.53	-2.53	-2.87	-3.53	-11.91	-14.67	-20.61
Constant (c)	-3.15	-3.48	-4.14	-3.18	-3.51	-4.18	-15.92	-18.85	-25.00
Constant & Trend (ct)	-3.66	-3.99	-4.66	-3.69	-4.03	-4.70	-21.13	-24.26	-30.64

Table 15: Static Least Squares (SLS) results for France and Germany, showing p-values for each variable.

Variable	France (P-Values)	Germany (P-Values)
const	0.0000	0.0001
Pop_density	0.0000	0.0000
Agri_percent_land	0.0001	0.0692
Cattleperkm	0.0000	0.7453
kWh_percapita	0.0036	0.9818
Fertilizer	0.1676	0.0091
Hydropower	0.0280	0.1852

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Table 16: Dynamic Ordinary Least Squares (DOLS) Results for France and Germany.

Country	Variables	Coefficients	P-Values	Details
France	const	160.055214	0.0000	Original
	Pop_density	-0.129820	0.9547	Original
	Agri_percent_land	-0.766031	0.0462	Original
	Cattleperkm	-0.205246	0.2739	Original
	kWh_percapita	0.000503	0.3693	Original
	Fertilizer	0.002658	0.8696	Original
	Hydropower	-0.016470	0.1120	Original
	Pop_density_lag	-0.744103	0.5510	Lag
	Agri_percent_land_lag	-0.993644	0.0048	Lag
	Cattleperkm_lag	0.206558	0.0092	Lag
	kWh_percapita_lag	-0.000451	0.4514	Lag
	Fertilizer_lag	-0.007311	0.5720	Lag
	Hydropower_lag	-0.009608	0.3471	Lag
	Pop_density_lead	0.384998	0.7335	Lead
	Agri_percent_land_lead	-0.108793	0.7667	Lead
	Cattleperkm_lead	0.319212	0.0900	Lead
	kWh_percapita_lead	-0.000931	0.3362	Lead
	Fertilizer_lead	-0.014422	0.3362	Lead
	Hydropower_lead	0.002517	0.8009	Lead
Germany	const	-40.641535	0.0039	Original
	Pop_density	0.118138	0.3498	Original
	Agri_percent_land	0.448009	0.1370	Original
	Cattleperkm	-0.126872	0.4409	Original
	kWh_percapita	0.001797	0.0025	Original
	Fertilizer	-0.025865	0.3967	Original
	Hydropower	-0.035452	0.3563	Original
	Pop_density_lag	-0.064942	0.4133	Lag
	Agri_percent_land_lag	0.238634	0.3174	Lag
	Cattleperkm_lag	0.172784	0.0449	Lag
	kWh_percapita_lag	-0.000791	0.0378	Lag
	Fertilizer_lag	-0.022088	0.4414	Lag
	Hydropower_lag	0.027068	0.5081	Lag
	Pop_density_lead	0.010284	0.8497	Lead
	Agri_percent_land_lead	-0.117079	0.6600	Lead
	Cattleperkm_lead	0.076041	0.5066	Lead
	kWh_percapita_lead	-0.000554	0.0421	Lead
	Fertilizer_lead	0.010316	0.1745	Lead
	Hydropower_lead	0.074172	0.0421	Lead

Table 17: Error Correction Model (ECM) results for France and Germany.

Country	Variables	Coefficients	Adjustment Coefficients
France	Emission	1.000000	-0.0021683
	Pop_density	0.343858	0.003212
	Agri_percent_land	-0.225945	0.044115
	Cattleperkm	-1.134520	0.035022
	kWh_percapita	-0.000314	-33.098602
	Fertilizer	0.124281	-1.718139
	Hydropower	-0.040602	-0.456119
Germany	Emission	1.000000	0.004905
	Pop_density	-0.515766	0.026130
	Agri_percent_land	3.439682	-0.017688
	Cattleperkm	-0.734607	0.043413
	kWh_percapita	0.001417	14.271561
	Fertilizer	-0.083136	0.095419
	Hydropower	-1.661595	0.110439

Table 18: FMOLS Results for France and Germany

Variables	**Coefficients (France)**	**Corrected SE (France)**	**P-Values (France)**	**Coefficients (Germany**
const	118.465650	28.558045	0.0000	−29.262211
$\text{Pop}_{d}ensity$	−0.386299	0.083888	0.0000	0.053078
$\text{Agri}_{p}ercent_{l}and$	−1.315049	0.322709	0.0001	0.417407
Cattleperkm	0.253778	0.056802	0.0000	0.133706
$\text{kWh}_{p}ercapita$	−0.000543	0.000235	0.0036	0.000340
Fertilizer	−0.011970	0.012213	0.1676	−0.0013526
Hydropower	−0.024103	0.014882	0.0280	−0.001194