Down by the Water
Multivariate Econometrics

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1 Literature review

1.1 Effect of Renewable Energy (RE) on Global warming and GHG emissions

For the sake of future generations, addressing environmental change has become essential to ensure a liveable and sustainable planet. Research has extensively shown that greenhouse gas (GHG) emissions, predominantly driven by fossil fuel-based CO_2 emissions, can be significantly reduced through the use of renewable energy sources (Justice et al., 2024). The adoption of renewable energy sources directly contributes to reducing reliance on fossil fuel-based power plants, which are currently responsible for approximately 35%–40% of all greenhouse gas emissions (Rahman et al., 2022).

Renewable energy (RE) deployment can have both positive and negative environmental impacts. A comprehensive study by Virah-Sawmy and Sturmberg (2025) reviewed the potential socioeconomic and environmental effects of several key RE sources. The study focused on the following energy sources: solar photovoltaic (PV), onshore and offshore wind farms, wave energy converters (WECs), tidal turbines, floating solar PV (FPV), hydro energy, and bioenergy.

Regarding negative environmental impacts, much can be attributed to terrestrial habitat alteration, marine habitat disruption, hydrodynamic changes, and impacts on water quality. For example, Hydropower plants are known to interfere with fish migration routes, as well as cause hydrodynamic changes such as wave scattering and wave radiation, in addition to altering hydrological cycles and water quality. Interestingly, the study notes that very few papers discuss the well-known global benefits of RE, such as carbon emission reduction. However, it also fails to highlight that each RE source can also produce CO_2 emissions throughout its entire life cycle. This includes emissions from raw material extraction, part production, use phase, and end-of-life (EoL) processes for systems and components.

1.2 CO_2 emission analysis of hydropower – closed system approach

A study by Bayazıt (2021) examined the effects of hydroelectric power plants on carbon emissions using the widely adopted Life Cycle Analysis (LCA) methodology, which assesses emissions at each stage of the power generation process. The average life cycle carbon equivalent density for a coal power plant is 820 gCO_2-eq/kWh, whereas a hydroelectric power plant produces approximately 18.5 gCO_2-eq/kWh. This indicates that hydroelectric power plants reduce greenhouse gas emissions by 97.7% compared to coal power plants. Additionally, hydroelectric power reduces greenhouse gas emissions by 96.2% per kilowatt-hour compared to natural gas, 92% compared to biomass, 61.5% compared to solar PV, and 51.3% compared to geothermal energy. This study used the well-known LCA software tool, SIMAPRO, to calculate emissions. However, a limitation of these types of LCA studies is that they analyze emissions from a closed-system perspective. Indirect environmental impacts, which may also be significant, are not captured by the model. As a result, studies that incorporate statistical and econometric methods can provide additional insights into the actual environmental benefits of renewable energy sources.

1.3 Use of statistical analysis to extract correlation causal analysis

A growing number of studies have investigated the impact of renewable energy (RE) sources on CO_2 emissions using time series and panel data models. Statistical modeling and regression analysis offer significant flexibility and potential advantages in assessing environmental impacts. The choice of data and statistical methods can emphasize different effects and may even reveal varying outcomes between cases. Below are several considerations for data usage and method selection that have been used in past studies to capture the effects of RE on CO_2 emissions.

1.3.1 Data selection

The choice of data included in the set is crucial for the potential research question. In panel data sets, multiple countries are analysed simultaneously, which adds more informative data, more variability, less collinearity, more degrees of freedom and more efficiency. The 38 OECD countries are the ones most often studied and accounted for 42.2% of global electricity generation in 2021 (Ritchie, 2021). Perone (2023) focused on panel data, including 27 out of 38 OECD countries. It must be noted that if one plans to panel data, he/she must account for cross-sectional dependence, and make use of certain assumptions. More on this is described later in the review. Furthermore, using either aggregated renewable energy sources, single energy sources or nonaggregated energy sources can also lead to varying results.

- Saidi and Omri (2020) focussed on aggregated renewable energy sources in 15 OECD countries.
- Güney (2022) focused solely solar energy as the main explanatory variable in a panel set of 35 countries, (non aggregated).
- Güney and Üstündağ (2021) selected wind energy as the primary independent variable (non aggregated) on a panel set of 37 countries.
- Bashir et al. (2023) concentrated on geothermal energy (non aggregated) in 10 newly industrialized countries.
- Destek and Aslan (2020) examined disaggregated renewable, including energy consumption in 7 countries.

Furthermore, Perone (2023) highlighted the importance of using energy production instead of energy consumption as an explanatory variable. This distinction can be crucial because energy production could have a potentially positive effect on CO_2 emissions, which contrasts with the traditional focus on energy consumption.

1.3.2 Unit root testing

Common tests for identification of a unit root (and thus non-stationarity) are the Augmented Dicky Fuller test (Dickey & Fuller, 1979) and the Phillips Perone (P. C. B. Phillips & Perron, 1988). The Phillips-Perron uses a nonparametric method to adjust the test statistics for serial correlation and heteroskedasticity. Another test is the The Robinson (Robinson, 1994) test, which differs from the ADF and PP test mainly by allowing more general forms of non-stationarity and testing for fractional integration with a null hypothesis that the series could be any I(d) process, where d can take fractional values. This approach captures long-memory processes that fall between strict stationarity (I(0) and non-stationarity with a unit root (I(1). The downside of this test is that even if you do have fractional unit roots, you can only perform (most) cointegration test on I(1) series anyway. A study by Harris (1992) on unit root testing compares the performance of the Augmented Dickey-Fuller (ADF) test across a range of simulated data-generating processes (DGPs) using Monte Carlo simulations and provides insights into selecting lag lengths in autoregressive structures, to test how often the ADF test rejects the null of non-stationarity when it is true (size) and when the alternative is true (power). The simulation considers various DGPs, such as AR, MA, and ARMA processes, with or without drift and trend components. Since 1992 Monte Carlo simulations have gained extreme popularity in model selection, as they tell a lot about the performance of a model in different scenarios. However, for lag length selection, a more common procedure nowadays is the use of Akaike Information Criterion (AIC). The Zivot Andrews (ZA) (Zivot & Andrews, 1992) test also tests for unit roots, but accounts also for structural breaks. Perone, as well as many other studies using panel data (such as also Güney and Üstündağ (2021), or Bashir et al. (2022)), used the Pesaran (2006) cross-sectionally augmented Dickey-Fuller (CADF) panel unit root test. Saidi and Omri (2020) used the Levin pooling cross-section time series data for testing the unit root. Not all studies decided to test for unit roots, for example Destek and Aslan (2020) stated that in their study it was not necessary due to the estimator it used (Augmented Group Mean), and Güney (2022) didn´t use or advocate for it in their study of solar energy effect on CO_2. In this study, since we are focusing on time series we illustrate the use of ADF, PP, ZA.

1.3.3 Cointegration analysis

In the context of analyzing the relationship between Hydro Energy Consumption (HEC) and CO_2 emissions, performing unit root and cointegration-analysis is essential for ensuring reliable and meaningful results in a time-series or panel data framework. This concept is described in the 1987 study of Engle and Granger. Since then, many studies have attempted to perfect or apply the theorem to different kinds of estimators. A study by Haug (1996) attempted to identify which cointegration test is most applicable in varying scenarios. It did so by applying Monte Carlo simulations to systematically compare size and power distortion. It compared the Engle and Granger´s-ADF cointegration test, the Phillips and Ourliaris Z test for a single cointegration relationship, both test are based on testing of stationarity (no-cointegration) of the residuals. Again, just as with the unit root test of Phillips and Perone, The difference is the use of nonparametric corrections in the latter. However, Haug found that the two tests are asymptotically equivalent. For multivariate cases, it compared the Stock and Watson test with the two Johansen test; 1. Johansen Trace and 2. Maximum Eigenvalue tests. Many of the calculations were described to be similar, but the two approaches differ. Johansen's approach uses the lag information in transforming, whereas Stock and Watson's approach uses only the covariance matrix. Also, Johansen's method employs likelihood analysis and assumes that errors are Gaussian. Haug found that more than one cointegration test should be applied, and that additional Monte Carlo simulations to test for weak exogeneneity of the study could help find accurate results. The more recent (applied) studies that concerned themselves with cointegration between CO_2 emissions and RE, made use of other tests more suitable to panel data, since often they were using large panel data sets. For example, Bashir et al. (2022), but also Güney (2022), used the Westerlund method of cointegration. The test reduces the application of common factor constraints on tests based on residual dynamics. Perone (2023) skipped the initial cointegration testing and proceeded directly with autoregressive distributed lag (ARDL) panel regression, which he then transformed to the ECM form to see long and short-term dynamics. In this study, working with multivariate time series data, we chose to perform firstly the Engle and Granger (Engle & Granger, 1987) approach and the Phillips-Ouliaris (B. Phillips & Ouliaris, 1990) test for single linear cointegrating vectors of variables. Then also the multivariate testing approach of the Johansen trace and maximum eigenvalue test is performed (Johansen, 1988).

1.3.4 Estimation and inference of cointegration relations

Kripfganz (2018) explaines that by using an ARDL model on multivariate data the variables can be stationary, nonstationary, or a mixture of the two types. He stated that In its equilibrium correction (EC) representation, the ARDL model can be used to separate the long-run and short-run effects, and to test for cointegration or, more generally, for the existence of a long-run relationship among the variables of interest. Perone also states that this is the main reason for using this method in his study. Perone further states that it included multiple variables in the model and optimizes the lag order by maximizing the log-likelihood function while minimizing the RMSE. Perone further refines the analysis by using the ARDL with panel-specific estimators to estimate dynamic heterogeneous panels. These estimators include Pooled Mean Group (PMG), Mean Group (MG), and Dynamic Fixed Effects (DFE). These estimators are only relevant when working with panel data, but are known to be outdated since the development of the CCEMG method of Pesaran. Perone also compared estimation with FMOLS, DOLS and the Pesaran´s CCEMG for robustness. For the FMOLS and DOLS models (which are time series models more than panel models). Perone used the panel group mean of Pedroni (2001). Perone chose not to look into system cointegration by applying the Johansen. Furthermore, earlier studies also often referred to FMOLS and DOLS, but not all:

Bashir et al. (2022) uses DFOLS and FMOLS on panel data of 10 countries, ignoring the cross-sectional dependence.

Güney and Üstündağ (2021) used the method of weighted fixed effect pooled estimator (WFE), OLS, and deviations from the mean (Pesaran and Yamagata 2008) on panel data of 37 countries, also ignoring the the cross-sectional dependence.

Güney (2022) used first differencing to eliminate unit roots on 35 countries, followed by Two-step GMM and IV (2SLS) estimates of model to account for endogeneity of the regressors.

Saidi and Omri (2020) used pooled cointegration analysis on 15 OECD Ccountries. We will use the FMOLS and DOLS to first regress the single cointegration relations, accounting for simultaneity and autocorrelation in the estimator.

1.3.5 Cointegration system

When dealing with more than 2 regressors in a system, there are more than 1 cointegration relations possible. However, non of the studies above decided to look into cointegration systems using the Johansen test, even though all of them used a multivariate regression. In this study, we will analyse full cointegration systems using Johansen methods.

1.3.6 Testing for Granger causality

Lastly the VECM can be used to test for granger causality. Perone uses The PVAR model, estimated via GMM, to handle interdependent variables while controlling for bias. However, before applying the PVAR, Perone says it is good practice in PVAR to take the first difference of all the variables to eliminate unit roots. This completely eliminates cointegration relations from the model, which is perhaps not the best thing to do when there are multiple unit roots found in the system. Later on in the paper, Perone says its variables lay outside the unit circle, and are therefore stationary. This is not coherent with the unit root test he did earlier on it the paper. He later states that they perform the Granger non causality on the PVAR model, but it is not clear if this is executed in the end on first difference- variables or on the I(1) level variables. In this study, we will correctly account for the occurrence of unit roots for the elaboration of a VECM model, and apply a Granger causality test to this multivariate cointegration system analysis.

1.3.7 Structural breaks

Engle and Granger's cointegration model assumes stable long-term relationships, which can be problematic if structural breaks shift the relationship. In such cases, models can extend to cointegration tests with structural breaks to identify whether a new long-term equilibrium relationship forms after the break. For instance, if a major environmental agreement changes emissions patterns, cointegration regressions that allow for structural breaks can more accurately reflect the new dynamics. In cases where structural breaks are suspected, incorporating break-adjusted error-correction models can help identify how quickly systems return to equilibrium post-break, capturing more accurate short-term dynamics. This will be accounted for in this study as well, applied to unique cointegration vector regressions, as well as cointegration system regressions.

1.4 Research gap

The novelty of Perone's study primarily lies in the use of a large panel dataset and the application of some panel-specific modeling and testing techniques. In contrast, this study focuses on multivariate time series methods to examine the specific effects in France and Germany. One mayor reason for also doing single country analysis is the bypassing of heterogeneity/ cross sectional dependence issues. Whereas Pesaran (2006) has shown that it is possible to account for the cross-sectional error dependence, there are always assumptions that have to be made that influence the results. The assumptions that have to be made are covariance stationary unobserved common factory, independent distribution of the individual specific errors, and independent and identically distributed factor loading. Of course these are assumptions made when using the CCEMG. In Perone, CCEMG is referred to as a robustness estimator, and he lists the GM, PGM, DFE as the main estimators of his study. These estimators do not account for individual specific effects, nor do they work when there are endogeneity problems or short time series. Lastly, the study of Perone does not account for cointegration systems through the use of Johansen trace and maximum eigenvalue analysis.

By adopting this alternative approach, we aim to provide more detailed and granular insights into the dynamics of these two countries. Also we aim to highlight differences in outcomes compared to the panel approach of Perone´s study. Additionally, through the application of multiple tests for unit roots and cointegration on both single-vector cointegration as well as cointegration systems, we aim to precisely identify the cointegrating relationship between hydropower and CO_2 emissions.

2 Graphical analysis of the data

2.1 Statistical analysis of the 7 regressors

In this section of the report we will compare plots of time-series data for the countries Germany and France and focus on characteristics such as the presence of deterministic trends and the order of integration. It is important to note here that we will first focus on the visual representation and conclusions of the data. In the following section we will confirm if our visual inspection and interpretation of the data can be confirmed by statistical tests.

2.1.1 Summary statistics

Below in table 1 and 2 the summary statistics of the 7 regressors for Germany and France respectively are listed.

Table 1. Summary Statistics for Germany

	Emission	Pop_density	Agri_percent_land	Cattleperkm	kWh_percapita	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	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

Note: This table presents the summary statistics for Germany, including indicators such as emissions, population density, agricultural land usage, cattle density, electricity consumption per capita, fertilizer usage, and hydropower reliance.

A comparison of the results reveals that Germany has higher average values for population density, CO_2emissions, cattle density, and per capita electricity consumption. In contrast, France, with a lower overall population density, shows lower averages for emissions, cattle density, and electricity consumption. However, France has higher averages for fertilizer usage, the percentage of agriculture land usage, and reliance on hydropower, while Germany demonstrates lower averages for these agricultural and renewable energy indicators.
In the research of Ayyildiz and Erdal (2021), similar results have been reported regarding the relationship between cattle density and CO_2 emissions. For instance, a study in Environmental Science and Pollution Research highlights that a 1 percentage increase in the livestock production index leads to a 0.81

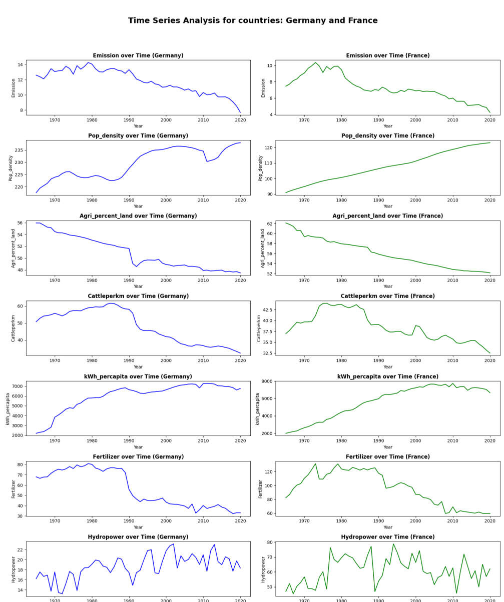
Table 2. Summary Statistics for France

	Emission	Pop_density	Agri_percent_land	Cattleperkm	kWh_percapita	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	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

Note: This table presents the summary statistics for France, including indicators such as emissions, population density, agricultural land usage, cattle density, electricity consumption per capita, fertilizer usage, and hydropower reliance.

percentage rise in CO_2 emissions. This supports our observation that Germany's higher cattle density corresponds to higher CO_2 emissions per square kilometer.
When examining the role of population density on CO_2 emissions, we find contrasting results in the literature. Higher population densities in urban areas are often associated with lower per capita CO_2 emissions due to increased use of public transport and compact living (Ogden et al., 1986). However, macro-level studies indicate that urbanization and higher population density are positively correlated with total energy consumption and overall CO_2 emissions, likely due to increased industrial activity and energy demand (Liddle, 2014). These contrasting findings may offer some insight into Germany's higher per capita emissions. While compact living and public transportation in urban areas can reduce individual emissions, the country's urbanization and industrial activities appear to outweigh these benefits. Alternatively, other factors might play a more significant role in determining CO_2 emissions, emphasizing the complexity of this relationship.

Figure 1: Time series analysis for Germany and France.



Note: Figure 1 displays data over time for the variables: emissions, population density, percentage of agriculture land usage, cattle density, electricity consumption per capita (kWh), fertilizer use, and hydropower usage over time for the countries Germany and France. On the x-axis we see the years from 1965 to 2020, on the y-axis we have the respective units for each variable. The graphs on the left, represented by a blue line, show the data for Germany, and the graphs on the right, represented by a green line, show the data for France.

The variables for both countries show similar patterns throughout history. Emissions, agricultural land percentage, cattle density per square kilometer, and fertilizer usage show a decrease over time, whereas population density and electricity consumption per capita increase. Hydropower usage shows a slight upward trend in Germany, but no noticeable increase in France.

2.1.2 Analysis of missing values or unusual trends

Based on visual inspection, there are no major problems with missing values or unusual trends. Each time series follows the expected patterns consistent with historical and economic developments, such as gradual declines in emissions and agricultural land use, along with increased electricity consumption per capita. For Germany, there is a noticeable drop around 1990 in the percentage of agricultural land, fertilizer use, and cattle density. A similar trend is visible in France, although the decline is not as sharp. This can largely be attributed to the European Nitrates Directive (1991), which set stricter standards for fertilizer use to protect water quality and reduce nitrate pollution. The sharper decline in Germany is likely due to the Düngeverordnung (Fertilizer Ordinance), which went a step further with more regulations. These additional regulations make the impact more visible in Germany compared to France.

2.1.3 Analysis of covariance stationarity

In order for a time-series to be covariance stationary, the variables should have a time independent mean, variance and auto-covariance.
Based on the first visual expectation of Figure 1, none of the variables appear to be covariance stationary. We observe an upward or downward trend in all the variables, which violates the constant mean assumption. Therefore, these variables cannot be covariance stationary. Only hydropower usage visually exhibits a constant mean and could possibly be covariance stationary. For research purposes and to answer these questions further, we decided to plot the first differences of all the variables. It is important to note that we are still relying on visual observations and must confirm these interpretations with statistical tests. In figure 5 from Appendix A we observe the first differences of the variables. All the variables seem to be stationary after differencing it, therefore based on the visual inspection we suspect all the variables to be integrated of I(1) and hydropower to be I(0) because of their stationary appearance without the differencing. None of the time series seem to be I(2).

2.1.4 Analysis of deterministic trends in the time series

A deterministic component such as a linear trend can be visually observed as a clear smooth upward or downward trend over time. Based on the visual inspection the variables: population density, percentage of agriculture land usage and kWh per capita over time might have a deterministic time trend. For research purposes we isolated the trend component by decomposition of the time series (Appendix A figure 4). Based on figure 4, all the time series exhibit an upwards or downwards trend, indicating there might be a deterministic trend in all the time series for both countries. Further, to analyze if our time series shows evidence in favor of a constant can be determined by looking at the average level of each variable over time. As can be seen in figure 1, the time series for variables have a non-zero mean, hence a constant is needed in our analysis to account for this.

2.1.5 Transformations to the time series

We decided not to apply log-transformations to our data. Based on the literature, Lütkepohl and Xu (2009), log transformation can help with skewed data and stabilizing variances, when there are large outliers to reduce variability. We log-transformed all the variables, figure 6 in Appendix A. Based on this figure, we observe taking the log transformation does not affect any of the plotted variables for both countries. Therefore we suggest not to apply logarithmic transformations when we purely base this on the visual inspection.

3 Analysis of the order of integration

3.1 Choice of deterministic components

As discussed in section 2.1.4, based on a graphical analysis of the data is concluded that the time series of all variables show evidence in favor of two deterministic components: a time trend and a constant. Including these deterministic components is crucial for validity and comparability of statistical tests. So, to overcome biased estimation of parameters and distortion of relationships between variables it is vital to include both these deterministic components in the model when conducting any time series analysis. Hence, in the rest of this paper a constant and a time trend component are included in the models to all the variables to assure reliable and interpretable results.

3.1.1 Autocorrelation and structural testing

To assure we are applying the correct Unit Root test based on the particularities of our data, such as autocorrelation in the residuals, and or structructural breaks in the time series, ACF and Bai-Perron test are executed. The result of the ACF test are presented in figure 2 and 3 for Germany and France respectively.

Figure 2: ACF of Residuals for 7 Variables for Germany

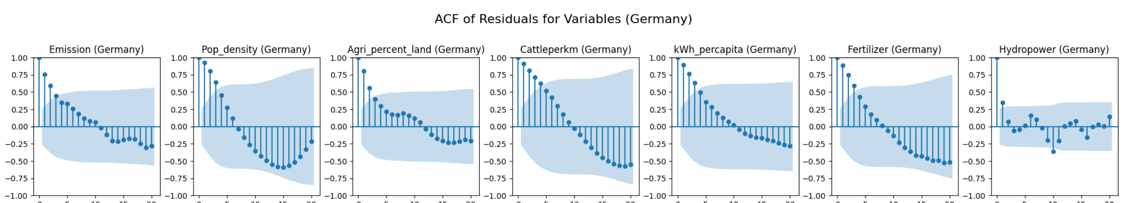
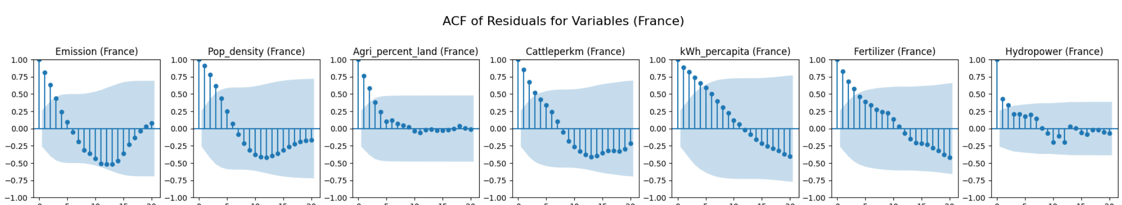


Figure 3: ACF of Residuals for 7 Variables for France



Note: Figure 2 and 3 display the autocorrelation functions for all 7 variables for Germany and France seperately. The plots show the correlation of the specified variable with itself at different lags. On the y-axis the autocorrelation coefficient is shown, ranging between 1 and -1. On the x-axis the number of lags is displayed, ranging from 0 to 20 lags. The blue dots show the coefficients for each lag. The light blue surplus shows the 95% confidence interval.

From the ACF plots of figure 2 and 3 can be concluded that blue dots, corresponding to autocorrelation coefficients, which are outside of the light blue confidence interval indicate statistical significant autocorrelation at a 5% significance level for the specified lags of the corresponding variable. This phenomenon is present for at least one lag in the ACF plots of all variables for both France and Germany, so it can be concluded that for all variables autocorrelation is present in the data. The persistence in autocorrelation for all variables in both Germany and France has lead us to exclude the Dickey Fuller test of our analysis and move straight to ADF and PP tests. Since these test are robust against autocorrelation, whereas the Dickey-Fuller test is not.

The results of the Bai-Perron test are depicted in table 3. For this we followed the methodology described by Bai and Perron (1998).

Table 3. Number of Structural Breaks by Bai-Perron Test

Variable	**Country.**	**Breaks**
Emission	Germany, France	2, 2
Pop_dens	Germany, France	5, 10
Agri_percent_land	Germany, France	3, 4
Cattleperkm	Germany, France	6, 5
kWh_percapita	Germany, France	10, 10
Fertilizer	Germany, France	7, 9
Hydropower	Germany, France	2, 9

Note: In table 3 the results of the Bai-Perron Test are shown. The table presents for each variable the number of structural breaks discovered in the data for Germany and France, respectively.

As is visible in table 3, all the variables seem to exhibit structural breaks. Therefore, we decided to include an additional third Unit Root test that is robust against structural breaks, the Zivot-Andrew test.

3.2 ADF, Phillips-Perron and Zivot-Andrews

As indicated in the last section, the three tests that were chosen in this study are the ADF, Phillips-Perron and the Zivot-Andrews test. In the literature review, it was already briefly mentioned that the ADF and PP differ in way of estimation. In this section we describe all methods briefly.

The Augmented Dickey-Fuller (ADF) test models the correlation in the errors by fitting an AR(p) process instead of an AR(1), to account for autocorrelation in further lags:

$$\Delta x_t = \mu + \beta t + (\lambda - 1)x_{t-1} + \sum_{j=1}^{k} \beta_j \Delta x_{t-j} + u_t$$

We test the null hypothesis:

$$H_0 : \lambda - 1 = 0$$

If k is specified correctly and if u_t is serially uncorrelated, then t_λ will have the same asymptotic distribution as in the serially uncorrelated case. To chose the optimal number of k the Akaike Information Criterion (AIC) is used to determine k.

The Phillips-Perron is a non parametric test that considers the difference between $T(\hat{\lambda} - 1)$ and the nuisance parameter dependent term in the limit, which should then have the same limiting distribution as in the serially uncorrelated case. We consider the following test statistic:

$$T(\hat{\lambda} - 1) - \frac{1}{2}\frac{\sigma_u^2 - \sigma_0^2}{\sigma_u^2}\int_0^1 [W(r)]^2\, dr \quad \xrightarrow{d} \quad \frac{1}{2}\frac{[W(1)]^2 - 1}{\int_0^1 [W(r)]^2\, dr}$$

where $\hat{\gamma}(0)$ and $\hat{\sigma}_u^2$ are consistent estimators for the unknown nuisance parameters, and $W(r)$ denotes a standard Brownian motion.

The Zivot and Andrew test is an alteration to the ADF and PP test, which utilizes the full sample and uses a different dummy variable for each possible break date. We used a package indicating a single break. The break date is selected where the t-statistic from the ADF test of unit root is at a minimum (most negative). The test has different critical values than the PP test. The test is applied to the following model:

$$y_t = \mu + \beta t + \theta D_t + (\lambda - 1)y_{t-1} + \sum_{j=1}^{k} \delta_j \Delta y_{t-j} + \epsilon_t$$

Which has roughly the same structure as the ADF, but including a dummy variable for the break.

Comparison of tests

The results are of the tests are displayed in Table 3. In Germany, we see that ADF and PP show I(1) for all variables except hydropower, which appears to be stationary. For France, we see all variables except Population density I(2) and hydropower and fertilizer (in case of PP) are I(1). The Zivot-Andrew test seems to vary more in results, showing 3 stationary variables in Germany (Agriculture, fertilizer and hydropower), and 1 in France (Hydropower).

Table 4. Stationarity Results for the ADF, PP, and Zivot-Andrews Tests for Germany and France

Country	Variable	ADF	PP	Zivot-Andrews
Germany	Emission	I(1)	I(1)	Non-stationary
	Pop_density	I(1)	I(1)	Non-stationary
	Agri_percent_land	I(1)	I(1)	I(0)
	Cattleperkm	I(1)	I(1)	Non-stationary
	kWh_percapita	I(1)	I(1)	Non-stationary
	Fertilizer	I(1)	I(1)	I(0)
	Hydropower	I(0)	I(0)	I(0)
France	Emission	I(0)	I(1)	Non-stationary
	Pop_density	I(2)	I(2)	Non-stationary
	Agri_percent_land	I(1)	I(1)	Non-stationary
	Cattleperkm	I(0)	I(1)	Non-stationary
	kWh_percapita	I(1)	I(1)	Non-stationary
	Fertilizer	I(1)	I(0)	Non-stationary
	Hydropower	I(0)	I(0)	I(0)

Note: Table 6 present the results of the ADF, PP, and Zivot-Andrews tests for all 7 variables for Germany and France. In the table I(0) indicates a stationary time series, I(1) achieved after first differencing and I(2) corresponds to a stationary achieved after second differencing.

The differences in assumptions can be described as follows. The ADF test does not incorporate structural breaks as something that can potentially influence the presence. PP does assume that they influence the test, therefore he accounts for them by inclusion of an exogenous nuisance parameter. Lastly Zivot-Andrew treats the structural break as endogenous, and estimates it as a dummy.

4 Cointegration Analysis

4.1 Expected cointegration relationships

According to the DOLS and FMOLS and CCEMG estimations of Perone, Hydropower is cointegrated with CO_2 at a high significance level. We chose to ignore the PMG and MG outcomes due to unsuitability to Perones studies and due to the fact that we did not perform analysis with these estimates.

Table 5. Cointegration Coefficients for Hydropower and CO_2 across Estimators in Perone

Estimator	Coefficient	Std. Error	Significance
FMOLS	-1.53	0.28	***
DOLS	-5.28	1.23	***
CCEMG	-0.0215	0.0101	**

Note: In table 5: '*', '**' and '***' indicate statistical significance at 10%, 5% and 1% significance level, respectively. Further, values in the table correspond to a model with CO_2 as dependent variable and Hydropower as regressor.

Other studies such as Al-Mulali et al. (2015), Sinaga et al. (2019), Waris et al. (2023) were also listed in the paper of Perone as studies that found cointegration between CO_2 and Hydropower. Unfortunately, the paper did not list which studies do not find cointegration. Destek and Aslan (2020) narrated that according to their AMG regression, 1% increase in hydropower reduces CO_2 emission by 0.295%, 0.063% and 0.072% in Italy, the UK and the US, respectively. However, they did not use cointegration analysis and just assumed stationarity of the variables. The other papers researched in this study showed cointegration relationships with other green power sources. From our previous analysis, hydropower was not I(1), therefore, we do not assume that it is cointegrated with CO_2. However, for the purpose of performing the analysis anyway, we assume that hydropower is I(1).

4.2 Single cointegration relation estimation

To analyse whether cointegration relationships between different variables are present in the data, two residual based cointegration tests are performed. The Engle and Granger method and the Phillips-Ouliaris Z^* test. Subsequently, to perform an analysis on the number of cointegration relationships that is present in the data a Maximum Likelihood based test is used, the Johansen test. The Johansen test consists of two different types, in this report both the Trace test as well as the Maximum Eigenvalue approach are used.

4.2.1 Engle and Granger Two-Step Method

The Engle and Granger Two-Step method is used to test for a cointegration relationships variables that are integrated of order 1. Specifically, this method tests for stationarity in the residuals of a static linear regression between a dependent non-stationary variable and multiple non-stationary regressors. If the residuals are stationary, this indicates that there exist a long run relationship between the dependent variable and the independent variables in the regression (Engle & Granger, 1987).

First, to conduct the Engle and Granger approach test a static regression is performed with the variable of interest, Emission, as dependent variable and the other 6 variables as independent variables, regressors. Additionally, as stated in section 2 the variables contain a clear determinstic trend. We account for this by including a time trend and a constant in the model, as can be seen in equation 1. The Ordinary Least Squares (OLS) regression method is used in this section to obtain parameter estimates.

$$\begin{aligned}\text{Emission}_t = \beta_0 + \beta_1\text{Hydropower}_t + \beta_2\text{PopDensity}_t + \beta_3\text{AgriPercentLand}_t + \beta_4\text{CattlePerKm}_t \\ + \beta_5\text{kWhPerCapita}_t + \beta_6\text{Fertilizer}_t + \gamma t + u_t\end{aligned} \tag{1}$$

Second, an Augmented Dickey-Fuller (ADF) test is performed on the residuals $\hat{u}_t$ to test for the existence a non-unit root according to the following equation:

$$\hat{u}_t = \rho\hat{u}_{t-1} + \epsilon_t, \tag{2}$$

where

$$\begin{aligned}\hat{u}_t = \text{Emission}_t - \hat{\beta}_0 - \hat{\beta}_1\text{Hydropower}_t - \hat{\beta}_2\text{PopDensity}_t - \hat{\beta}_3\text{AgriPercentLand}_t \\ - \hat{\beta}_4\text{CattlePerKm}_t - \hat{\beta}_5\text{kWhPerCapita}_t - \hat{\beta}_6\text{Fertilizer}_t - \hat{\gamma}t.\end{aligned} \tag{3}$$

The hypothesis for the Engle and Granger two-step method are:

- Null hypothesis (H_0): $\rho = 1$, a unit root is present in the residuals, no cointegration.
- Alternative hypothesis (H_1): $\rho < 1$, a unit root is not present in the residuals, a cointegration relationship exists between the two variables y_t and x_t.

Since $\hat{u}_t$ is not raw data but is based on the estimates of the integrated x_t process, the asymptotic distribution of the t-statistic is shifted to the left. To account for this, the critical values of McKinnon (1991) are used.

4.2.2 Phillips-Ouliaris Z* Test

The Phillips-Ouliaris cointegration test uses a similar approach as the Engle and Granger Two-Step method. The main difference between the two tests lies within the distribution of the estimated cointegrating residuals. The Phillips-Ouliaris test states that, because of the spurious regression problem, the estimated cointegrating residuals do not exhibit the Dickey–Fuller distributions under the null hypothesis of no-cointegration. To account for this, the Phillips-Ouliaris test uses a different asymptotic distribution with its own critical values, this was also described for the PP unit root test in section 3. The paper of B. Phillips and Ouliaris (1990) provides tabulated critical values corresponding to models with a constant and trend with up to 5 independent variables. However, in the model of interest (equation 1) there are 6 independent variables. So, in this report the Phillips-Ouliaris critical value is obtained through a Monte Carlo simulation approach where non-stationary time series are repeatedly generated, then a Phillips-Ouliaris cointegration test is conducted, then analyzing the test statistics under H_0 of no cointegration, and subsequently calculating the empirical percentiles to derive critical thresholds.

4.3 Johansen cointegration system test

The earlier discussed residual based methods test whether there exists a single linear cointegration relationship. It therefore assumes that the cointegration relation between the variables is unique, which is not always the case. The Johansen Trace and Maximum Eigenvalue tests are both Maximum Likelihood based tests that can be used to analyse a system of cointegration relationships in the data.

The Johansen test is used in case of a multivariate statistical method of n-variables, with a minimum of n = 3 variables, assuming all n variables to be integrated of order 1. The test is used to discover the number of cointegrating relationships in the system, which can be at most n - 1 relationships. In addition, in case of cointegration of more than 2 variables, the Johansen test estimates the cointegrating vectors by Maximum Likelihood estimation (Dwyer, 2015).

The Johansen test is based on the VECM, which is derived from a Vector Autoregressive (VAR) model of order k:

$$\Delta \mathbf{y}_t = \Gamma \mathbf{y}_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta \mathbf{y}_{t-i} + \varepsilon_t, \tag{4}$$

The number of lags (k) used in the model is determined by the Hannan-Quinn Criterion (HQIC). The dataset consist of a relative small amount of observations, which increases the risk of overfitting by including too many parameters. Hence, the HQIC is chosen over the AIC to avoid overfitting. Also, in this approach the maximum number of lags is limited based on the rule of thumb $max(k) = T^{1/3}$, to avoid the issue of overfitting due to too many parameters even more.

Matrix Γ can be decomposed in elements α and β, as can be seen in equation 5.

$$\Gamma = \alpha \beta' \tag{5}$$

In this equation α represent the loading matrix, showing the adjustment coefficients and β represents the cointegration matrix, containing cointegration vectors. The rank (r) of the Γ matrix indicates the number of cointegrating relationships. (Johansen, 1988).

To identify r the Johansen approach uses two test statistics, the trace test and the maximum eigenvalue test. These two methods are both based on the eigenvalues of Γ, which are computed according to equation 6.

$$\det(\Gamma - \lambda I_n) = 0 \tag{6}$$

The obtained eigenvalues can be ordered on size, $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_k$. If $\lambda_i = 0$, this means that rank(Γ) = 0, indicating $i-1$ cointegrating vectors. Subsequently, the first eigenvalue λ_i that is equal to zero identifies the number of cointegrating vectors, which will then be equal to $i-1$. The methodology is to start at testing $\lambda_1 > 0$, if this holds $\lambda_2 > 0$ is tested. If this does not hold, then the number of cointegrating relationships is equal to $1-1=0$. To determine the rank of Γ two different approaches are used, the trace test and the maximum eigenvalue test.

4.3.1 Trace Test

The trace test determines the amount of cointergrating relationships r, by evaluating the hypothesis:

$\mathbf{H_0}$**:** $(H_0 : r \leq r_0)$, there are a maximum of r cointegrating vectors.
$\mathbf{H_a}$**:** $(H_a : r > r_0)$, there are a more than r cointegrating vectors.

These are tested with the following test statistic:

$$\text{Trace statistic} = -T \sum_{i=r_0+1}^{n} \ln(1-\lambda_i),$$

The trace test starts at testing $r_0 = 0$. This will increase sequentially with 1 rank until the null hypothesis is not rejected.

4.3.2 Maximum Eigenvalue Test

Further, the maximum eigenvalue test evaluates the amount of cointegrating relationships by testing:

$\mathbf{H_0}$**:** $(H_0 : r = r_0)$, this implies exactly r cointegrating vectors.
$\mathbf{H_a}$**:** $(H_1 : r = r_0 + 1)$.

The test statistic is computed as:

$$\text{Maximum eigenvalue statistic} = -T \ln(1-\lambda_{r_0+1}),$$

As stated before, the eigenvalues are ordered on size, so in the equation above λ_{r_0+1} is equal to the (r_0+1)-th largest eigenvalue. Moreover, the maximum eigenvalue test is conducted by sequentially increasing r until the null hypothesis is not rejected. Both the trace test and maximum eigenvalue test are performed on critical values provided by Johansen (1988).

4.4 Cointegration test results

Table 6. Cointegration Test Results for the Engle and Granger Approach and the Phillips-Ouliaris Z$*$ Test for Germany and France

Country	Test	Test Statistic	Critical Value (95%)	Decision
France	Phillips-Ouliaris	-3.873	-4.047	Do not reject H_0 (Evidence of No Cointegration)
France	Engle and Granger	-4.007	-4.982	Do not reject H_0 (Evidence of No Cointegration)
Germany	Phillips-Ouliaris	-2.242	-4.047	Do not reject H_0 (Evidence of No Cointegration)
Germany	Engle and Granger	-4.115	-4.982	Do not reject H_0 (Evidence of No Cointegration)

Note: In table 6, 7 and 8 the decision regarding the rejection of H_0 shown is derived from comparing the determined test statistic with the corresponding critical value at 5% significance level. Consequently, this indicates the final outcome of the specified test at a 5% significance level. Further, in table 7 and 8 'G' refers to Germany, while 'F' refers to France.

Table 7. Trace Test Results for Germany and France

Rank (r*)	Trace Statistic (G)	Trace Statistic (F)	Critical Value (95%)	Decision (G)	Decision (F)
0	135.62	174.95	111.78	Reject	Reject
1	89.52	117.53	83.94	Reject	Reject
2	51.73	78.82	60.06	Fail to Reject	Fail to Reject
3	32.56	46.11	40.17	Fail to Reject	Fail to Reject
4	15.15	24.76	24.28	Fail to Reject	Fail to Reject
5	4.95	10.41	12.32	Fail to Reject	Fail to Reject
6	0.55	0.71	4.13	Fail to Reject	Fail to Reject

Table 8. Maximum Eigenvalue Test Results for Germany and France

Rank (r*)	Max Eigenvalue (G)	Max Eigenvalue (F)	Critical Value (95%)	Decision (G)	Decision (F)
0	46.10	57.41	42.77	Reject	Reject
1	37.78	38.72	36.63	Reject	Fail to Reject
2	19.18	32.71	30.44	Fail to Reject	Fail to Reject
3	17.41	21.35	24.16	Fail to Reject	Fail to Reject
4	10.20	14.35	17.80	Fail to Reject	Fail to Reject
5	4.39	9.69	11.22	Fail to Reject	Fail to Reject
6	0.55	0.71	4.13	Fail to Reject	Fail to Reject

As stated before, both the Engle and Granger approach and the Phillips-Ouliaris test test for whether a cointegrating relationship can be found in the model as specified in equation 1. In table 6 can be seen that for both tests the H_0 is not rejected, indicating no evidence of no cointegration in the data for both France and Germany.

Further, the Johansen method tests for the number of cointegrating vectors using the trace test and the maximum eigenvalue test, giving information about possible multiple cointegrating vectors. From the test results in table 7 and 8 can be seen that that Germany the lowest rank for which the null hypothesis is not rejected is $r^* = 3$. This result implies that both the trace test and the maximum eigenvalue test provide statistical evidence in favor of 3 cointegrating vectors. Further, in the results for France a difference in outcomes is observed. The trace test fails to reject the null hypothesis of $r^* = 3$, whereas the maximum eigenvalue test fails to reject the null hypothesis of $r^* = 2$.

4.5 Evidence in favor or against cointegration

From the Engle and Granger approach we can conclude that the model does not find a long run cointegrating relationship between Emission and the other variables for both Germany and France, while including a constant and a time trend, as specified in equation 1. The test results for the Phillips-Ouliaris Z* test performed on the same model are in line with the result of no cointegrating of the Engle and Granger approach.

However, as can be seen in table 6 and 7, the Johansen Trace test and Maximum Eigenvalue test do find statistical evidence in favor of multiple cointegrating vectors. In the data for Germany 3 cointegrating vectors are found in both tests. For France the Trace test results in 3 cointegrating vectors, while the Maximum Eigenvalue test indicates 2 vectors with a long run equilibrium.

4.6 Estimation cointegration

4.6.1 Static Least Squares

The static least squares is method to estimate the cointegrating relationship between variables for only a single cointegrating vector. This approach does not account for dynamic effects or simultaneity for the independent variables. The resulting estimator is superconsistent for the coefficients and remains consistent regardless of the chosen normalization. The formula for the Static Least Squares is displayed below (7). This equation captures the long-run relationship between CO_2 emissions and the independent variables related to hydropower and other factors.

$$
\begin{aligned}
\text{Emission}_t = {} & \beta_1 \text{Hydropower}_t + \beta_2 \text{PopDensity}_t + \beta_3 \text{AgriPercentLand}_t \\
& + \beta_4 \text{CattlePerKm}_t + \beta_5 \text{kWhPerCapita}_t + \beta_6 \text{Fertilizer}_t + u_t
\end{aligned} \tag{7}
$$

The results, displayed in table 9 show that hydropower plays a significant role in reducing emissions in France, while it has little to no impact in Germany. This suggests that hydropower may be more effective in reducing emissions in certain contexts. Both countries also show strong links between emissions, agricultural land use, and livestock density. However, the presence of residual autocorrelation suggests that the results may not be entirely reliable, and more robust methods are needed to confirm these findings.

Table 9. Static OLS Regression Results for Germany and France

Variable	Germany Coef.	p-value	France Coef.	p-value
Constant	-29.262	**0.012**	118.466	**0.000**
Hydropower	-0.0012	0.974	-0.024	**0.028**
Pop density	0.053	0.083	-0.386	**0.000**
Agri percent land	0.417	**0.016**	-1.315	**0.000**
Cattle per km^2	0.134	**0.000**	0.254	**0.000**
kWh per capita	0.0003	0.075	-0.0005	**0.004**
Fertilizer	-0.0135	0.476	-0.012	0.168
Durbin-Watson	0.758		0.877	

Note: P-values below 0.05 are in bold.

4.6.2 Dynamic Ordinary Least Squares

Dynamic OLS (DOLS) improves on ordinary least squares (OLS) by adding a vector k, containing I(0). By adding this stationary regressors the asymptotic distribution change and this makes it more tractable. Further, this eliminates a part of the bias as well. This helps to address issues like endogeneity and serial correlation, resulting in more reliable estimates of the long-run relationships. However, it does not fully solve the problem of simultaneity, where the regressor and the error term are jointly determined.

The estimated regression equation is specified as follows.

$$
y_t = \alpha + \beta x_t + \sum_{k=-p}^{q} \gamma_k \Delta x_{t+k} + \epsilon_t
$$

Choosing the number of lags for the model involves balancing the need to capture sufficient information while avoiding overfitting. Autocorrelation in the residuals for both Germany and France indicates that multiple lags are necessary to capture the dynamics, and the HQIC suggests that 3 lags are optimal. Based on this, we decided to include 3 lags in the model.

Table 10. Dynamic OLS Regression Results for Germany and France

Variable	Germany Coef.	p-value	France Coef.	p-value
Constant	-19.9796	**0.023**	82.2610	**0.011**
Hydropower	-0.0144	0.620	-0.0196	0.084
Pop density	0.0578	**0.043**	-0.3136	**0.001**
Agri percent land	0.2484	0.058	-0.7634	0.061
Cattle per km^2	0.1225	**0.000**	0.1761	**0.008**
kWh per capita	7.516e-05	0.595	-0.0004	0.139
Fertilizer	-0.0009	0.959	-0.0199	**0.048**
Durbin-Watson	1.298		0.728	

Note: P-values below 0.05 are in bold.

The results of the DOLS regression are displayed in table 10. Among the predictors for Germany, population density and cattle per km^2 are significant contributors to emissions. However, hydropower, fertilizer, and kWh per capita are not significant, suggesting that these factors do not have a measurable long-term impact on emissions in Germany. The Durbin-Watson statistic (1.298) indicates mild residual autocorrelation, which could affect the robustness of the results.

Population density, use of fertilizer livestock per km^2 significantly influence emissions in France. While, agricultural land and hydropower approach are not significant at 5% level. Hydropower is also not significant. Furthermore, fertilizer is significant and negatively associated with emissions, suggesting its role in mitigation. The Durbin-Watson statistic (0.728) indicates significant residual autocorrelation.

4.6.3 Fully Modified Ordinary Least Squares

Autocorrelation occurs when error terms are correlated across time what violates the assumption of independent errors. FMOLS accounts for this by using non-parametric corrections to the residuals. It uses the covariance matrix of the innovations to neutralize the effects of serial correlation on the parameter estimates. It provides asymptotically unbiased and efficient estimates of long-run relationships. This ensures the asymptotic efficiency of the estimator. Compared to DOLS, FMOLS avoids the inclusion of lags, offering an alternative perspective on long-run dynamics.

Further, simultaneity arises because the dependent variable $x_{1,t}$ and the regressors $x_{2,t}$ are cointegrated, leading to the effects between them. FMOLS corrects for this by the conditional error term

$$\frac{1}{T}\sum_{t=1}^{T}\mathbf{x}_{2,t}\vartheta_t \xrightarrow{d} \int_0^1 \mathbf{B}_2(r)d\mathbf{B}_{1.2}(r)+\delta$$

using

$$\delta = \Sigma_{21}+\Lambda_{21}-(\Sigma_{22}+\Lambda_{22})\Omega_{22}^{-1}\Omega_{21},$$

Additionally, serial correlation, represented by Ω_{22}, is addressed using kernel-based estimators that account for the long-run variance in the residuals.

Table 11. FMOLS Regression Results for Germany and France

Variable	**Germany Coef.**	**p-value**	**France Coef.**	**p-value**
Constant	-18.572	**0.015**	85.364	**0.008**
Hydropower	-0.0123	0.729	-0.018	0.092
Pop density	0.058	**0.031**	-0.304	**0.002**
Agri percent land	0.231	0.074	-0.901	**0.025**
Cattle per km^2	0.119	**0.001**	0.193	**0.003**
kWh per capita	0.0002	0.401	-0.0003	0.073
Fertilizer	0.0021	0.892	-0.011	0.178
Durbin-Watson	1.32		0.89	

Note: P-values below 0.05 are in bold.

In the case of Germany, significant predictors include population density and livestock. Hydropower, agriculture percentage of land, fertilizer, and kWh per capita remain insignificant, indicating limited measurable impact on emissions in the long run. The Durbin-Watson statistic (1.32) suggests minimal autocorrelation. This supports the robustness of these results.

In the case of Germany, the population density, agricultural land, and cattle per km^2 significantly impact emissions. Hydropower, fertilizer and KWh per capita are not significant. The Durbin-Watson statistic (0.89) indicates small autocorrelation. Significant predictors such as population density and cattle per km^2 reflect consistent drivers of emissions across Germany and France.

4.6.4 Error Correction Model (ECM): Long-Term Effects (β's)

The Error Correction Model (ECM) combines short-run dynamics with the adjustment toward long-run equilibrium in cointegrated systems. It includes an error correction term, derived from the lagged residuals of the cointegrating equation, to account for deviations from the long-run relationship. Unlike methods such as FMOLS and DOLS, the ECM explicitly incorporates both short-term dynamics and the adjustment process toward equilibrium. In this analysis, we used three lags to maintain consistency with the methods reported earlier.

Step 1: Cointegrating Regression (OLS) The long-term equilibrium relationship is estimated as:

$$Emission_{i,t-1} = \beta_0^i + \sum_{j=1}^{k} \beta_j^i X_{j,i,t-1} + \epsilon_{i,t},$$

where:

- $X_{j,i,t-1}$ represents the explanatory variables (e.g., Hydropower, Population Density, etc.),
- β_j^i are the long-term effects (coefficients) for country i,
- β_0^i is the constant (intercept term).

The residuals from this regression are used to construct the Error Correction Term (ECT):

$$ECT_{i,t-1} = Emission_{i,t-1} - \hat{\beta}_0^i - \sum_{j=1}^{k} \hat{\beta}_j^i X_{j,i,t-1}.$$

The Error Correction Model incorporates the ECT term to capture deviations from the long-term equilibrium:

$$\Delta Emission_{i,t} = -\lambda_1 \cdot ECT_{i,t-1} + \sum_{j=1}^{k} \sum_{p=1}^{3} \theta_{j,p} \Delta X_{j,i,t-p} + \epsilon_{i,t},$$

where:

- $-\lambda_1$: Speed of adjustment toward the long-term equilibrium,
- $\Delta X_{j,i,t-p}$: First differences of the explanatory variables lagged by p periods (up to 3 lags),
- $\theta_{j,p}$: Short-term effects of the j-th variable at lag p.

The β_j^i's represent the long-term effects of each explanatory variable on emissions.

Table 12 summarizes the estimated long-term effects (β's) and their statistical significance for Germany and France.

Table 12. Error Correction Model (ECM) Results for Germany and France (Long-Term Effects Only)

Variable	**Germany ($\hat{\beta}$)**	**Germany p-value**	**France ($\hat{\beta}$)**	**France p-value**
Constant	-0.1599	0.090	-0.2629	0.194
Hydropower (β_1^i)	-0.0693	0.082	-0.0094	0.075
Pop density (β_2^i)	0.1871	0.063	-0.0760	0.926
Agri percent land (β_3^i)	0.3807	0.196	-0.2341	0.287
Cattle per km² (β_4^i)	0.1454	0.199	-0.0181	0.800
kWh per capita (β_5^i)	0.0013	**0.009**	0.0006	0.066
Fertilizer (β_6^i)	-0.0267	0.255	0.0059	0.473
ECT ($-\lambda_1$)	-0.1387	0.513	-0.0542	0.642
Durbin-Watson	2.314		1.535	

Note: P-values below 0.05 are in bold.

In Germany, energy use (kWh per capita) is the only significant long-term predictor with a positive coefficient. This suggests that energy use plays a key role in driving emissions over time. Hydropower is not significant, so no clear relationship with emissions can be established. The error correction term (ECT) is also not significant, suggesting a weak adjustment to deviations from the long-term equilibrium.

In France, none of the predictors, including hydropower, show significant long-term associations with emissions. This means no conclusions can be drawn about their impact. Similarly, the ECT is not significant, indicating that emissions do not strongly return to the long-term equilibrium after short-term changes.

4.7 The differences between the assumptions of used methods

Static Least Squares assumes the residuals from the cointegrating regression are stationary I(0). This method does not correct for the endogeneity in the regressors and serial correlation. This is its main limitation. Also, it does not present adjustments for short-run dynamics or long-run equilibrium. Dynamic Least Squares corrects for endogeneity by adding lags of first-differenced regressors to the cointegrating regression. It assumes that lags capture all short-run dynamics and that the residuals are stationary I(0). Therefore, this method accounts for a serial correlation unlike SLS. The fully modified OLS is a method that adjusts for both endogeneity and serial correlation by using non-parametric corrections based on long-run variance. It also produces efficient estimates in the case of cointegration. Error Correction model combines short and long run dynamics into one model. It assumes that cointegrating residuals influence short-run dynamics. Long-run dynamics are represented by the error correction term. It also assumes that deviations from the long-run equilibrium adjust over time.

In summary, the models differ in relation to the correction for bias (endogeneity and serial correlation) and focus. By the focus it is meant that each model is centered on estimating only long-run relationships (SLS) or both short and long-term dynamics (ECM)

4.8 Cointegration system analysis; Johansen's Analysis VECM

The Vector Error Correction Model (VECM) is represented as:

$$\Delta \mathbf{y}_t = \Gamma \mathbf{y}_{t-1} + \sum_{i=1}^{2} \Gamma_i \Delta \mathbf{y}_{t-i} + \mathbf{v}_t,$$

where:

- $\mathbf{y}_t = [\text{Emission}, \text{Hydropower}, \text{PopDensity}, \text{AgriPercentLand}, \text{CattlePerKm}, \text{kWhPerCapita}, \text{Fertilizer}]^\top$ is the vector of endogenous variables.
- $\Gamma = -\alpha\beta'$, where:
  - β' is the cointegrating matrix capturing the long-term relationships between the variables,
  - α is the matrix of adjustment coefficients describing how each variable reacts to deviations from the equilibrium.
- $\Gamma_i = -\sum_{j=i+1}^{p} \Phi_j$, which accounts for short-term dynamics with lagged differences of $\mathbf{y}_t$.
- $\mathbf{v}_t$ is the vector of error terms.

Johansen's cointegration analysis identifies long-term equilibrium relationships among variables in a multivariate setting. This method applies the Vector Error Correction Model (VECM), derived from a Vector Autoregressive (VAR) model, to account for both short-term dynamics and long-term relationships. Further, we accounted for a structural break for emissions in 2020 for both countries based on the Zivot-Andrews test from section 3. The ranks were derived from the trace test. For Germany (r=3) and France (r=3).

For the estimation of the (β) and (α), estimated cointegrating coefficients (β) representing the equilibrium relationships and adjustment coefficients (α) indicating the speed of convergence toward equilibrium.

To estimate the cointegration relationships and adjustment coefficients in a multivariate time series, we followed a structured approach:

First we prepared the data by calculating the first differences of the time series, the lagged levels of the data and the lagged differences used to capture short-term dynamics. We solved the eigenvalue problem and obtained the residuals by the maximum likelihood estimation with the orthogonal idempotent matrix M:

$$\left|\lambda S_{hh} - S_{h0} S_{00}^{-1} S_{0h}\right| = 0, \tag{8}$$

$$S_{00} = \frac{1}{T} R_0' R_0, \quad S_{0h} = \frac{1}{T} R_0' R_h, \quad S_{hh} = \frac{1}{T} R_h' R_h. \tag{9}$$

Then, we solved for eigenvalues and eigenvectors of:

$$S_{h0}S_{00}^{-1}S_{0h} \quad \text{relative to} \quad S_{hh}. \tag{10}$$

The beta's were normalized and the adjustment coefficients were estimated as follow:

$$\hat{\beta}' S_{hh} \hat{\beta} = I_r, \tag{11}$$

$$\hat{\alpha} = -S_{0h}\hat{\beta}. \tag{12}$$

These coefficients describe the speed and direction of adjustment back to equilibrium after deviations.

The results are presented in the Table 13 and 14.

Table 13. Break-Adjusted Cointegration and Adjustment Coefficients for Germany

Variable	**Cointegrating Coefficients ($\hat{\beta}$)**			**Adjustment Coefficients ($\hat{\alpha}$)**		
	Vector 1	**Vector 2**	**Vector 3**	**Vector 1**	**Vector 2**	**Vector 3**
Emission	1.9223	-1.1502	-1.0508	0.0578	-0.1112	-0.1175
Hydropower	-0.8037	0.1501	0.0781	0.1754	0.6034	0.1479
Pop Density	0.0500	-0.1603	-0.0803	0.2326	-0.1003	-0.0520
Agri Percent Land	-0.3231	1.0050	0.5780	-0.0497	0.0163	-0.0999
Cattle Per Km^2	0.0317	0.3160	-0.2278	0.1841	0.0165	-0.2213
kWh Per Capita	0.0012	-0.0004	0.0003	55.6367	-45.2140	33.3961
Fertilizer	-0.2220	-0.2859	0.1387	-0.3716	-1.5193	0.2425
break_dummy	0.0000	0.0000	0.0000	-0.0249	-0.0341	-0.0080

Note: Coefficients estimated using Johansen VECM framework with structural break.

Table 14. Break-Adjusted Cointegration and Adjustment Coefficients for France

Variable	**Cointegrating Coefficients ($\hat{\beta}$)**			**Adjustment Coefficients ($\hat{\alpha}$)**		
	Vector 1	**Vector 2**	**Vector 3**	**Vector 1**	**Vector 2**	**Vector 3**
Emission	1.2588	0.7955	0.0056	0.0495	-0.0044	0.0143
Hydropower	-0.2660	0.0089	-0.0411	-1.4403	-0.1510	-2.3438
Pop Density	0.2162	0.0761	-0.6057	0.0098	0.0011	-0.0167
Agri Percent Land	0.3209	0.0187	0.9950	-0.0107	0.0408	0.0134
Cattle Per Km^2	-1.0975	-0.5455	0.8258	-0.1253	-0.3829	-0.0971
kWh Per Capita	0.0004	-0.0006	0.0017	72.6773	-43.9525	5.0744
Fertilizer	0.0563	0.1081	-0.2301	0.6609	0.7789	-1.7814
break_dummy	0.0000	0.0000	0.0000	-0.0339	0.0059	-0.0291

Note: Coefficients estimated using Johansen VECM framework with structural break.

The Johansen method helps in modeling complex and interdependent relationships. It also captures multiple cointegrating vectors at the same time. It contrasts with single-equation approaches like DOLS or FMOLS. Those also lack the capacity to analyze short-term dynamics and interrelations. Johansen method provides insights into both long-term equilibrium and short-term adjustments which is crucial for understanding emissions and energy dynamics in both countries. In conclusion, while single-equation methods offer simplicity and precision in estimating targeted relationships, system-based approaches like Johansen and VECM are useful for capturing the complexity of interrelated variables.

Further for a robustness we performed the Ljung-Box test on the residuals. No autocorrelation was found in this test for the residuals, suggesting a good lag specification for the model.

Table 15. Cointegration and Adjustment Coefficients for Germany

Variable	Cointegrating Coefficients ($\hat{\beta}$)			Adjustment Coefficients ($\hat{\alpha}$)		
	Vector 1	Vector 2	Vector 3	Vector 1	Vector 2	Vector 3
Emission	-2.2410	-1.6578	-1.2330	-0.0384	-0.0677	-0.1014
Hydropower	0.7860	0.0171	0.0358	-0.1253	0.5896	0.1010
Pop Density	-0.0259	-0.0555	-0.0303	-0.2495	-0.0934	-0.0477
Agri Percent Land	0.2652	0.6065	0.3703	0.0559	0.0139	-0.0999
Cattle Per Km^2	0.0227	0.3936	-0.2063	-0.1384	0.0890	-0.2043
kWh Per Capita	-0.0013	-0.0007	0.0001	-62.8548	-42.7478	35.0266
Fertilizer	0.2205	-0.2377	0.1736	0.2118	-1.5684	0.2978
Break Dummy	0.0000	0.0000	0.0000	-0.0249	-0.0341	-0.0080

Note: MLE estimates for VECM.

Table 16. Cointegration and Adjustment Coefficients for France

Variable	Cointegrating Coefficients ($\hat{\beta}$)			Adjustment Coefficients ($\hat{\alpha}$)		
	Vector 1	Vector 2	Vector 3	Vector 1	Vector 2	Vector 3
Emission	1.2813	-0.6415	-0.2784	0.0701	0.0057	0.0248
Hydropower	-0.2496	-0.0406	0.0291	-2.0825	0.1426	-2.2177
Pop Density	0.1420	-0.0268	-0.5898	0.0055	0.0011	-0.0190
Agri Percent Land	0.4285	-0.0191	0.8268	-0.0062	-0.0418	0.0079
Cattle Per Km^2	-0.9771	0.3738	1.0368	-0.1481	0.3650	-0.0177
kWh Per Capita	0.0004	0.0006	0.0014	75.7066	50.1990	2.1438
Fertilizer	0.0378	-0.0902	-0.2361	0.3626	-0.5999	-1.9455
Break Dummy	0.0000	0.0000	0.0000	-0.0340	0.0059	-0.0291

Note: MLE estimates for VECM.

4.8.1 Empirical interpretation of results

The results align with prior expectations regarding the relationship between emissions, hydropower, and other variables. Cointegrating coefficients ($\hat{\beta}$) highlight long-term relationships, with emissions showing positive associations with variables like hydropower, which contribute to long-term emission trends. Adjustment coefficients ($\hat{\alpha}$) indicate the speed of adjustment to equilibrium after shocks, while the structural break in 2020 captures external disruptions.

In Germany, the break-adjusted VECM reveals emissions as a central variable in all three long-term relationships, with the highest absolute $\hat{\beta}$ values (greater than 1). Emissions also show a moderate speed of adjustment, highlighting their role in restoring equilibrium. Hydropower plays a significant role, and in the break-adjusted model, its $\hat{\beta}$ shifts from positive to negative, indicating its mitigating effect on emissions. The structural break is appropriately captured but has minimal direct impact on system dynamics.

Similarly, for France, emissions remain the most critical variable in long-term relationships. Hydropower also plays a key role, influencing both long-term and short-term dynamics. In both countries, the break-adjusted VECM reveals that external shocks, such as the 2020 disruption, and policies like renewable energy promotion, can alter equilibrium relationships. In Germany, this is evident in hydropower's shift to a negative $\hat{\beta}$, contributing to emission reductions.

5 Granger causality

Granger causality is an important concept in econometrics, particularly in the analysis of time series data. Introduced by Granger in 1969, it examines whether past values of a variable X have explanatory power for current values of another variable Y. Importantly, Granger causality does not imply a direct causal relationship but rather identifies predictive relationships within the data (Eichler, 2007).

The literature emphasizes the importance of testing Granger causality in a multivariate context. Methods such as the Vector Error Correction Model (VECM) and Vector Autoregressive (VAR) approaches are commonly applied. The VECM is particularly suited for cointegrated variables because it accounts for long-term equilibrium relationships, while the VAR model, applied to first differences, focuses on short-term dynamics and disregards long-term relationships (Lütkepohl, 2005).

Following Al-Mutairi et al. (2014) and Bello et al. (2018), we applied the Granger causality with a VECM framework by distinguishing between short-run and long-run causality. For the long-run analysis, we focused not strictly on Granger causality as defined but rather on the effect of a variable on the system and its ability to help restore long-run equilibrium. The significance of long-run effects was determined by testing the significance of the adjustment speed coefficient (α) of the lagged ECT coefficient using the t-statistic. If this value larger than $|1.96|$ the result was significant. We tested the significance of the short-run Granger causality by using the Wald test for significance of the lagged first differences of the variables at a 95% confidence level. We estimated a VECM model from part 4.5, the number of lags were determined by estimating the VAR model (3), and the rank from the trace tests (3) for both Germany and France. The VECM model incorporated structural breaks for the variable emissions, for robustness check (see appendix A) a model without this structural break was tested as well. The ECT t-statistic in the table is the first variable of the α's for simplicity and interpretation.

Table 17. Structural Break Adjusted VECM Germany Granger Causality Test Results with Lags of 3

Dependent Variable	Emission	Pop_density	Agri_percent_land	Cattleperkm	kWh_percapita	Fertilizer	Hydropower	**ECT t-statistic**
Emission	–	**0.02**	**0.0**	**0.0009**	**0.0385**	0.324	0.3485	**-3.3558**
Pop_density	0.1497	–	**0.0075**	**0.0048**	0.2118	**0.0**	**0.0178**	**-4.1179**
Agri_percent_land	0.1503	**0.0075**	–	0.2616	**0.005**	**0.0**	**0.0**	**-4.5966**
Cattleperkm	0.7247	**0.0048**	0.2616	–	**0.0209**	**0.0**	**0.0002**	**-2.4999**
kWh_percapita	**0.0385**	0.2118	**0.005**	**0.0209**	–	**0.0**	**0.0002**	-0.2887
Fertilizer	0.324	**0.0**	**0.0**	**0.0**	**0.0**	–	**0.0**	-0.5174
Hydropower	0.3485	**0.0178**	**0.0**	**0.0002**	**0.0002**	**0.0**	–	-0.5174

Note: In table 17 the dependent variable is the caused variable, in the first column you find the causing variable. The values in the first part of the are the p-values from the wald test for the short run granger causality. On the most right column you find the ECT t-statistic. The bold values are corresponding as well with the significant values.

Table 18. Structural Break Adjusted VECM France Granger Causality Test Results with Lags of 3

Dependent Variable	Emission	Pop_density	Agri_percent_land	Cattleperkm	kWh_percapita	Fertilizer	Hydropower	**ECT t-statistic**
Emission	-	**0.0001**	**0.0**	0.0907	**0.0**	**0.0**	0.0513	-1.5625
Pop_density	**0.0063**	-	**0.0024**	0.401	**0.0**	0.518	**0.0136**	0.2909
Agri_percent_land	**0.0316**	**0.011**	-	0.0582	**0.0006**	**0.0**	**0.0**	**-4.8625**
Cattleperkm	0.18	**0.0**	**0.0001**	-	**0.0**	**0.0001**	**0.0023**	**4.7696**
kWh_percapita	**0.0024**	**0.0068**	**0.0**	**0.0084**	-	0.2449	**0.0**	**-2.6797**
Fertilizer	**0.0003**	0.0179	**0.0**	**0.0008**	**0.0001**	-	**0.0232**	0.0063
Hydropower	0.0513	**0.0**	**0.0**	0.1578	**0.0039**	**0.0232**	-	1.1132

Note: In table 18 the dependent variable is the caused variable, in the first column you find the causing variable. The values in the first part of the are the p-values from the wald test for the short run granger causality. On the most right column you find the lagged ECT t-statistic. The bold values are corresponding as well with the significant values.

In Germany, There is no granger causality of Hydropower on emission on the short term or the long term (p=5%). Emissions are significantly Granger-caused by kWh per capita in the short run. Emissions Granger-cause population density, agricultural land use, cattle per km$^{\mathbf{2}}$, and kWh per capita, indicating a bilateral Granger-causal relationship between emissions and kWh per capita. This could reflect how shifts in urbanization or agricultural practices are associated with variations in CO_2 emissions, potentially through energy demand or land-use changes. However, emissions are not Granger-caused by variables other than kWh per capita, indicating that emissions are a better predictor themselves rather than being predicted by other variables. In the long run, the results for emissions differ. The significant error correction term

(ECT) t-statistic value suggests that emissions contribute to restoring the long-run equilibrium after a shock. This indicates that long-term trends in emissions provide predictive information for restoring the long-run equilibrium relationship.

Regarding hydropower usage, this variable is significantly Granger-caused in the short term by all variables except emissions in the model with structural breaks. This suggests that past values of population density, agricultural land use, cattle per km^2, and kWh per capita provide useful information for predicting short-term changes in hydropower consumption, possibly reflecting adjustments in energy policies. However, hydropower usage does not Granger-cause emissions in the short run, indicating that variations in hydropower do not help predict emissions. When we compare our results **with the VECM model without structural breaks** (Appendix A, Table 17), we observe notable differences. For the variable emissions, more variables are Granger-caused by emissions in the short run in the model without structural breaks. However, in this model, the ECT for long-run Granger causality is no longer significant for emissions. For hydropower usage, this variable is Granger-caused by all variables in the model without structural breaks, unlike the model with structural breaks, where emissions do not Granger-cause hydropower usage in the short term. These results indicate that the Granger causality test is sensitive to structural breaks in the data. Accounting for structural breaks leads to more nuanced insights, particularly in distinguishing short-term and long-term causal relationships.

In France, There is no granger causality of Hydropower on emission on the short term or the long term (p=5%). There seems to be a bilateral granger causality relation between emissions and population density, agriculture land use, kWh per capita and use of fertilizer. There is a predictive power from emissions to those variables and vice versa. When observing the ECT t-statistics the values for the long run causality are not significant for both emissions and hydropower usage, meaning they do not provide predictive information for the long run equillibrium during this period. This highlights that the presence of short run causality does not indicate the presence of long run causality.

When we compare this **with the VECM model which does not account for structural breaks** (Appendix A table 18) we observe similar results, but also that hydropower and emissions have a significant bilateral granger causality relationship in the short term. This indicates that changes in hydropower usage provide valuable information for forecasting short-term emissions levels and vice versa. Possibly due to shifts in the energy mix when hydropower generation fluctuates. Conversely, emissions do not Granger-cause hydropower usage, meaning that emissions levels are not helpful for predicting short-term adjustments in hydropower consumption.

Concluding, when accounting for structural breaks in the VECM model, we get different results compared to the model without the structural breaks.

6 Comparison with Perone

As was stated in the literature review section, the study of Perone has a different setup than the present study. In this chapter we first explain the differences in data and in methodologies and assumptions. Finally we describe the differences in the result of the present study and Perone's study.

6.1 Data and methodology

For this study, it was chosen to only look at data from France and Germany separately. Therefore, no individual specific effects methods have been applied in this study. Furthermore, the focus of this study lies on hydropower, instead of multiple RE sources. Luckily, since the study of Perone was on disaggregated energy sources, we can still directly compare Perones estimates of Hydropower production. The control variables in both studies are kept the same for comparison purposes as well.

6.1.1 Unit root testing, and cointegration for single cointegration vector analysis

Perone used the Pesaran CADF test for the unit root testing, which accounts for cross-sectional dependence. As a sensitivity check, the panel unit root test developed by Karavias and Tzavalis (2014) was employed to account for structural breaks. We found this to be very reasonable choices. However, for this study, since this was a time series and not a panel analysis, we chose other unit root tests (PP, ADF, ZA) and separately tested for structural breaks using the Bai-Perron tests. Cointegration analysis was essentially applied using the Engle and Granger method, and the Phillips-Ouliaris Z* Test. These test both use the 2 step method, essentially applying Unit root tests to the residuals of the static multivariate regression. Although the different tests concluded different unit root results, in general Hydropower did not appear to have a unit root for either of the countries of our analysis, which is the same result of Perone. The other variables showed mostly I(1), which also is similar to the results of Perone. However, our additional Zivot Andrew test, which accounted for a structural break as an endogenous dummy variable, showed stationarity for 2 additional variables (fertilizer and agriculture). The presence of a single unit root is important for estimation of cointegration. The cointegration results of our Engle and granger and PP test showed no sign of cointegration between CO2 and Hydropower. However, performing additional cointegration system analysis through the Johansen test revealed that there were 3 cointegration vectors to be found in the system comprising of 6 variables. Perone did not perform these test, therefore no direct comparison is possible.

6.1.2 Estimation for cointegration

Perone used the GM, PGM and DFE estimators to account for individual specific effects in its 27 OECD country study, and applied them to an ARDL model (which is also rewritten in an ECM model). He also states to have used the CCEMG as a robustness check estimator. Due to the nickel bias, often described in literature, we believe that the CCEMG should have been Perone´s main estimator in his study. It must be noted that no such estimators have been used in this study, due to the focus on time series analysis. The use of time series estimates such as SLS, DOLS, FMOLS, and ECM we believe, gives better results for single-country time series analysis. Luckily, Perone also used FMOLS and DOLS in its analysis. This allows us to compare the results of the same estimates. To do this on the 27 countries, the study chose to apply a grouped mean to both the FMOLS and DOLS. Again it should be noted that with this, Perone is essentially ignoring cross-sectional dependence.

Perone´s study shows significant negative relationships for the FMOLS, DOLS and CCEMG estimations of hydropower with CO2. In this study none of the estimators show significant cointegration results between hydropower and CO2, for both France and Germany at the 5% significance level. At 10% significance however, all estimates show significant relations between Hydropower and CO2 in the country of France. The results of this are described in table 19. The results of the estimates in Perone were earlier already shown in Table 5. The results of this study however, rely on the assumption that all variables are integrated of order 1. Which goes against the Unit root analyses performed in this study, which show that Hydropower in both France and Germany are stationary.

Table 19. Cointegration Coefficients for Hydropower by Different Estimation Methods for Germany and France

Variable	Germany Coef.	p-value	France Coef.	p-value
SOLS	-0.0012	0.974	-0.024	**0.028**
DOLS	-0.0144	0.620	-0.0196	0.084
FMOLS	-0.0123	0.729	-0.018	0.092
ECM	-0.0693	0.082	-0.0094	0.075

Note: P-values below 0.05 are in bold. The results in table 19 correspond to a model with CO2 as dependent variable and Hydropower as regressor as specified in equation (7).

6.1.3 Granger causality

Perone uses the PVAR method to study Granger causality in panel dynamics. To avoid spurious regressions, the I(1) variables in this model must be differenced which limits the analysis to short-term Granger causality. Using this methodology, Perone found significant granger causality between Hydropower and CO2. In this research, we use the VECM approach, which captures both short-term and long-term Granger causality. This approach avoids the loss of information caused by differencing. Additionally, we account for the effects of structural breaks on the results, which Perone's method does not consider.

Our results for granger causality between hydropower and CO2 emission can be summarized as followed: In Both France and Germany, Emissions are not Granger caused by hydropower according to our study, which depends on the VECM model that is robust with structural breaks.

The short-run significance of granger causality was tested by Perone, using the first difference of the PVAR coefficients. In our VECM model that does not account for structural breaks, on the short term hydropower does granger cause CO2 emissions. Thus giving the same results as Perone.

From these results in can be concluded that the inclusion of structural breaks, the use of time series or panel series model and the analysis of long verses short term dynamics significantly influence results. Hence, in research of causality between hydropower and it can be stated that different methods allow for different insights on the environmental impact of RE sources such as hydropower. Also, the varying particularities of countries regulatory landscapes and RE production infrastructure make isolated analysis of emission factors complicated.

7 Ethics

When analyzing the relationship between certain variables, in our report hydropower usage and CO_2 emissions, one should be mindful of the consequences of misinterpreting data or drawing unfounded conclusions.

Data quality issues, which can be caused by errors, missing variables or outdated sources can mislead the analyses and lead to incorrect conclusions. This can be problematic if policy makers base their decisions on those incorrect analysis.

Ethical dilemma: farmers and people who work or live in the cattle or agriculture industry, if your analysis find a false causal relationship or you are not aware of spurious regressions for example, you can falsely recommend policy makers which can lead to new policies and can affect people and their lives.

To prevent certain events, it is important that we use data from reliable sources like government databases or reviewed studies. Further we should be aware of how the data is collected and always check the data by plots to identify outliers, structural breaks or missing variables which can affect the outcomes. Using different statistical tests can give different outcomes like we observed in part III. We should be aware of this and have funded arguments for which test will be the most valid/likely to be true. It is important to note this uncertainty in your recommendation to the policy makers. And it is important to link your findings to the current literature for more context.

To incorporate ethical considerations into your econometric modeling and policy recommendations regarding renewable energy adoptions. It is important to highlight the limitations of your analysis. Be transparent to policy makers where different results came from different tests, what solid parts of the analysis are and what the uncertain parts are. Include also the non-statistical significant parts.

8 Work load

We divided the work load for this assignment, we all read the Perone literature for comparison and read and double checked the entire document, and helped each other with the difficult tasks per section. Emma did most of the literature research and was in charge of the structure of the document, the part I and the comparison with Perone. Niels did part IV, and double checked part III. Marta did part III, the last questions of part IV and double checked part IV. Tess did part II and part V and double checked the document.

Appendix A

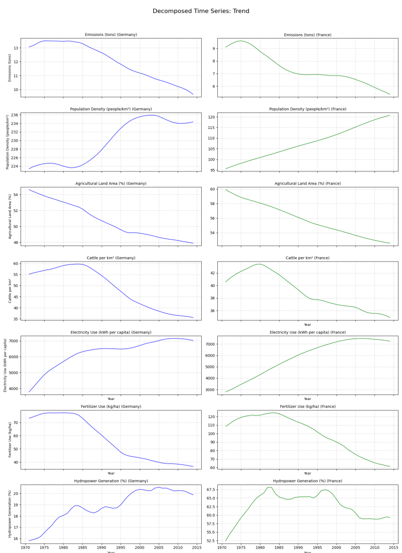


Figure 4: Graph of trend of the variables.

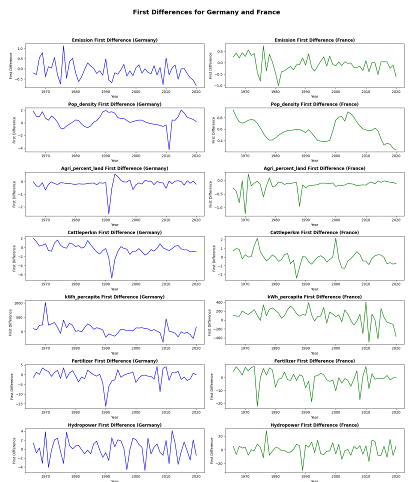


Figure 5: Graph of first differenced variables.

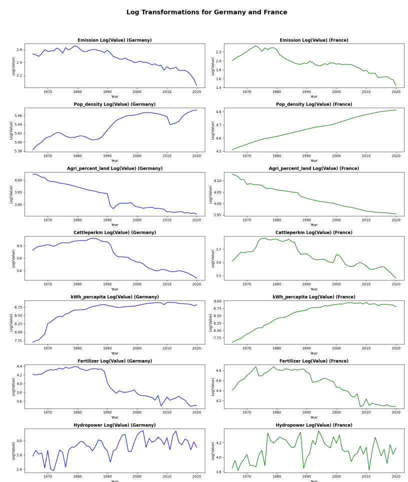


Figure 6: Graph of log-transformed variables.

Table 20. VECM Germany Granger Causality Test Results with Lags of 3

Dependent Variable	Emission	Pop_density	Agri_percent_land	Cattleperkm	kWh_percapita	Fertilizer	Hydropower	**ECT_t-statistic**
Emission	-	**0.0148**	**0.0**	**0.0138**	**0.0**	**0.0**	**0.0**	-0.3804
Pop_density	0.0565	-	**0.0002**	**0.0**	0.9751	**0.0**	**0.0**	**-3.5534**
Agri_percent_land	0.169	**0.0074**	-	0.3072	0.0689	**0.0**	**0.0**	**2.5801**
Cattleperkm	0.0828	**0.0038**	0.3072	-	**0.0192**	**0.0017**	**0.0023**	-0.8602
kWh_percapita	**0.0421**	0.2191	**0.0**	**0.0192**	-	0.1654	**0.0**	**-4.8290**
Fertilizer	0.067	**0.0**	**0.0**	**0.0**	**0.0002**	-	**0.0039**	-0.9883
Hydropower	0.1209	**0.0136**	**0.0**	**0.0023**	**0.0001**	**0.0039**	-	-0.6652

Table 21. VECM France Granger Causality Test Results with Lags of 3

Dependent Variable	Emission	Pop_density	Agri_percent_land	Cattleperkm	kWh_percapita	Fertilizer	Hydropower	**ECT_t-statistic**
Emission	–	**0.0001**	**0.0**	**0.0004**	**0.0014**	**0.0002**	**0.0276**	-1.0874
Pop_density	**0.009**	–	**0.0108**	**0.0**	**0.0073**	**0.0132**	**0.0**	**-4.7137**
Agri_percent_land	**0.0166**	**0.0108**	–	**0.0001**	**0.0**	**0.0**	**0.0**	**-4.8625**
Cattleperkm	0.1011	**0.0**	**0.0001**	–	**0.0006**	0.1103	0.3404	**4.7696**
kWh_percapita	**0.0014**	**0.0073**	**0.0**	**0.0006**	–	**0.0**	**0.0**	**-2.6797**
Fertilizer	**0.0002**	**0.0132**	**0.0**	0.1103	**0.0**	–	**0.0216**	-0.5174
Hydropower	**0.0276**	**0.0**	**0.0**	0.3404	**0.0**	**0.0216**	–	0.9730

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