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Three Essays on Energy Econometrics

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Abstract

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Three Essays on Energy Econometrics

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This study explores the relationship between energy markets, environmental factors, and economic performance. In the first chapter, we follow a two-step procedure (cointegration and spillover) to investigate energy market dynamics. We find a substitution (complementarity) relationship between fossil fuels and wind (solar) energy, driven by a growing environmental, social, and governance (ESG) sentiment. In the second chapter, we develop a panel data model to identify the path of energy consumption in Europe, then study the determinants of CO2 in a context of decarbonization that Europe is experiencing, finding evidence in the positive effect of renewable energy consumption. In the third chapter, we build a time-varying model to identify the role of temperature in shaping the gas demand and inflation for Euroarea. Our main result reports the significant role of temperature in containing the price surge. Finally, we provide some policy implications for governments and financial advices for investors.

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Principal Notation

Notation	Meaning	Ref. Equation
	Chapter 1	
$\boldsymbol{y}$	Vector of endogenous variables of the VECM	Eq (1.1), (1.2)
$\boldsymbol{Exo}$	Vector of exogenous and dummy variables of VECM	Eq (1.1)
$\boldsymbol{\zeta}$	Vector of errors from the VECM	Eq (1.1), (1.2)
$\boldsymbol{c}$	Deterministic component of the VECM	Eq (1.1)
p	Lag of the VECM model	Eq (1.1)
$\Pi = \alpha\beta'$	Cointegration (long-run) matrix	Eq (1.1), (1.2)
Γ	Short-Run VECM estimates	Eq (1.1)
$\mathcal{B}$	Exogenous parameter estimation VECM	Eq (1.1)
$\Delta\boldsymbol{y}_t$	First-Difference of $\boldsymbol{y}_t$	Eq (1.1), (1.2)
β	Cointegration vector	Eq (1.2)
α	Loading Factors	Eq (1.2)
$\boldsymbol{z}$	Vector of endogenous variables of the Bi-VAR	Eq (1.3)
$\boldsymbol{d}$	Deterministic component of the Bi-VAR	Eq (1.3)
$\boldsymbol{\nu}$	Vector of errors from the Bi-VAR	Eq (1.3)
L	Lag operator	Eq (1.4)
$\boldsymbol{\Theta}(L)$	Inverted matrix Lag-operator	Eq (1.4)
$\mathbf{I}_k$	Identity matrix of order k	Eq (1.4)
$\mathbf{Q}$	Lower triangular Cholesky factor of the covariance of $\boldsymbol{\nu}_t$	Eq (1.5)
$E(\boldsymbol{A}_0\boldsymbol{A}_0')$	Error covariance estimation	Eq (1.7)
$\boldsymbol{\epsilon}_{t+1}$	One-step ahead error vector	Eq (1.7)
$a_{0,11}$	Variance effect of own z_1 shocks	Eq (1.7)
$a_{0,12}$	Variance effect of z_2 shock on z_1	Eq (1.7)
$a_{0,21}$	Variance effect of z_1 shock on z_2	Eq (1.7)
$a_{0,22}$	Variance effect of own z_2 shocks	Eq (1.7)
$\boldsymbol{BiS}$	Bi-variate VAR total spillover index	Eq (1.8)
$\boldsymbol{x}$	Vector of endogenous variables of the VAR	Eq (1.10)
K	Is the number of column of the $\boldsymbol{x}$ vector	Eq (1.10)

$\boldsymbol{\varepsilon}$	Vector of errors from the generalized VAR	Eq (1.10)
$\boldsymbol{\Phi}$	Matrix of estimated Companion form VAR	Eq (1.10)
$\boldsymbol{\Psi}$	Matrix of estimated VMA	Eq (1.11)
$\theta^{g}_{i,j}(H)$	KPPS H-step ahead forecast error variance decomposition	Eq (1.12)
σ^{-1}_{jj}	Standard deviation of the error term for the j-th Eq	Eq (1.12)
$\boldsymbol{\epsilon}_i$	Selection vector with 1 as the i-th element and 0 otherwise	Eq (1.12)
$\boldsymbol{\epsilon}_j$	Selection vector with 1 as the j-th element and 0 otherwise	Eq (1.12)
$\boldsymbol{\Sigma}$	Covariance matrix for the vector $\boldsymbol{\varepsilon}_t$	Eq (1.12)
$\tilde{\theta}^{g}_{i,j}(H)$	Scaled forecast error variance decomposition	Eq (1.13)
$\boldsymbol{TSI}^{g}(H)$	Total Spillover Index	Eq (1.14)
$\boldsymbol{S}^{g}_{i.}(H)$	Series i TO Volatility Spillover Index	Eq (1.15)
$\boldsymbol{S}^{g}_{.i}(H)$	Series i FROM Volatility Spillover Index	Eq (1.15)
$\boldsymbol{S}^{g}_{i}(H)$	Series i NET Volatility Spillover Index	Eq (1.16)
$\boldsymbol{S}^{g}_{i,j}(H)$	Net Pairwise Volatility Spillover Index	Eq (1.17)
ω	Frequency decomposition of the BK method	Eq (1.18)
$\boldsymbol{R}_X(\omega)$	Power spectrum of $\boldsymbol{x}$ at frequency ω	Eq (1.18)
$\Psi(e^{-i\omega})$	Frequency response function obtained as Fourier transformation	Eq (1.18)
$\mathbb{F}(\omega)_{k,j}$	Spectral GFEVD on the ω frequency	Eq (1.19)
$(\boldsymbol{\Theta}_d)_{k,j}$	Generalized Variance Decompositions on frequency band d	Eq (1.20)
$(\tilde{\boldsymbol{\Theta}}_d)_{k,j}$	Scaled generalized variance decomposition on the frequency band d	Eq (1.21)
$\boldsymbol{S}^{W}_{d}$	Overall Spillover on frequency band d	Eq (1.22)
$\boldsymbol{S}^{F}_{d}$	Aggregate overall Spillover on frequency bands	Eq (1.23)

Chapter 2

y_{it}	Dependent variables of panel diagnostic tests	Eq (2.2), (2.8)
$x_{1,it}$	First regressor of the Slope Heterogeneity test	Eq (2.2)
$x_{2,it}$	Second regressor of the Slope Heterogeneity test	Eq (2.2)
β_{1i}	First vector $(k_1 \times 1)$ of slope coefficients	Eq (2.2)
β_{2i}	Second vector $(k_2 \times 1)$ of slope coefficients	Eq (2.2)
Δ	Slope heterogeneity test statistic	Eq (2.3)
$\hat{\beta}_{2i}$	Pooled OLS Estimation of Eq (2.2)	Eq (2.4)
$\hat{\beta}_{2,FE}$	FE Estimation of Eq (2.2)	Eq (2.4)
$\mathbf{M}_{1i}$	Projection matrix which include the constant and $x_{1,it}$	Eq (2.4)
σ^2_i	Unit specific variances of cross-section	Eq (2.4)
$\tilde{\Delta}$	Bias adjusted Slope heterogeneity test statistic	Eq (2.5)

Δ_{HAC}	Heteroskedastic and serial correlated Slope Heterogeneity test	Eq (2.6)
$\hat{\beta}_{2,HAC}$	Robust HAC estimator of β_2	Eq (2.6)
$\hat{\mathbf{Q}}_{\mathbf{it}}$	Projection matrix to bias the heterogeneous variables	Eq (2.6)
$\hat{\mathbf{V}}$	HAC correction for the slope heterogeneity test	Eq (2.6)
x_{it}	Regressors of Cross-Dependence test	Eq (2.8)
e_{it}	Error term from Cross-Dependence test	Eq (2.8)
ρ	Product-moment correlation coefficient of the error	Eq (2.9)
CD	Cross-dependence test	Eq (2.11)
CD(s)	Weak cross-sectional dependence test	Eq (2.12)
$\omega(\rho)_{ij}$	Is the i, j-th element of the proximity matrix of CD(s) test	Eq (2.12)
y	Endogenous variable CADF test	Eq (2.13), (2.16)
Δy	First-Difference of y, as Eq (1.2)	Eq (2.13), (2.16)
d	Deterministic component	Eq (2.13), (2.16)
$\bar{y}$	Cross-section avareges	Eq (2.13)
ε	Error-term of CADF and ECM	Eq (2.13), (2.16)
x	Exogenous variables of ECM	Eq (2.16)
λ_i	ECM loading factor	Eq (2.17)
f	Common Factors	Eq (2.18)
y	Dependent variable of CCEMG	Eq (2.18)
x	Independent variables of CCEMG	Eq (2.18)
u	Error-term structure of CCEMG	Eq (2.18)
β_i	Heterogeneous slopes CCEMG	Eq (2.18)

Chapter 3

$\boldsymbol{y}_t$	Endogenous TVPVAR n-dimensional vector	Eq (3.1)
$\boldsymbol{\vartheta}_t$	TVPVAR Companion matrix	Eq (3.1)
$\boldsymbol{\varepsilon}_t$	TVPVAR error term	Eq (3.1)
$\boldsymbol{\Omega}_t$	Error term covariance matrix	Eq (3.1)
$\boldsymbol{\Phi}_t = \text{vec}(\boldsymbol{\vartheta}_t)$	Random-walk process identification	Eq. (3.2)
$\boldsymbol{\nu}_t$	Random-walk error term	Eq. (3.2)
$\boldsymbol{\Sigma}_t$	Random-walk error term covariance matrix	Eq. (3.2)
$\boldsymbol{\Phi}_0$	Prior initialization	Eq. (3.3)
κ_1	ε_t discounting factor - Kalman filter parameter	Eq. (3.4)
κ_2	Random-walk convariance matrix discounting factor - Kalman filter parameter	Eq. (3.4)
γ	Parameters of TVPVMA representation	Eq (3.12)

ϱ	Generalized Impulse-Response Function via TVP estimation	Eq (3.13)
$\boldsymbol{\lambda}$	Standard deviation of the error term	Eq (3.13)
$\boldsymbol{\epsilon}_j$	Selection vector	Eq (3.13)
$\boldsymbol{\theta}_{ij,t}(H)$	Generalized Forecast Error Variance Decomposition	Eq (3.14)
$\Psi_{\nu,s}(t)$	Wavelet: real-valued square-integrable function	Eq (3.16)
$\mathbf{L}^2$	Hilbert space	Eq (3.16)
$1/\sqrt{b}$	Normalization factor ensuring unit wavelet variance	Eq (3.16)
b	Scale of the wavelet	Eq (3.16)
ν	Location parameter	Eq (3.16)
$\Psi_M(t)$	Morlet Wavelet	Eq (3.17)
ω_0	Frequency of the Wavelet	Eq (3.17)
$\mathbf{W}_x(\nu,b)$	Continuous Wavelet Transform (CWT)	Eq (3.18)
$\lvert\mathbf{W}_x(\nu,b)\rvert^2$	Local wavelet power spectrum (scalogram)	Eq (3.20)
$\mathbf{W}_{x,y}(\nu,b)$	Cross-wavelet transformation (XWT)	Eq (3.21)
$R^2_{x,y}(\nu,b)$	Wavelet coherence	Eq (3.22)
S	Smoothing operator	Eq (3.22)
$\zeta_{x,y}$	Phase difference	Eq (3.23)
$R^2_{x,y\|z}$	Partial Wavelet Coherence	Eq (3.24)
$\zeta_{x,y\|z}$	Partial Phase difference	Eq (3.25)

Introduction

This thesis aims to discuss the main issues in energy economics. Given the current interest in the subject, we aim to investigate about some particular features of this field, starting from its relevance in financial markets.

Recent literature describes the influence of energy uncertainty on financial markets.[1] While Xu et al. (2021) used a factor augmented vector autoregression model to construct a time-varying global energy market uncertainty, Dang et al. (2023) introduced the Energy-Related Uncertainty Index (EUI), based on previous work by Afkhami et al. (2017) using text search.

Given the current increase in global social awareness of financially sustainable products and the discussion on ESG principles that should be followed by companies, we propose to test two crucial hypotheses:

- financial markets have been increasingly influenced by the energy sector;
- renewable energies are increasingly integrated into financial markets, especially from the perspective of hedging and portfolio optimization.

Consequently, the remarkable impact of the financial energy series could be used to understand investors' choices and increase their knowledge of the subject.

In this sense, we discuss "sustainable finance"[2] as an evolving financial approach that conducts capital into renewable energy initiatives and supports the energy transition. It shapes the course of economies and the environment.

Governments and regulations are trying to promote the use of renewable energy to reduce fossil fuel consumption (Shen et al., 2010; Schaffer and Bernauer, 2014). Switching to renewable energy can significantly reduce air pollution (Omer, 2008;

[1] Among others, some notable recent works are Reboredo and Uddin (2016), Naeem et al. (2020), and Wang et al. (2023b).

[2] This concept is extensively discussed in Fatemi and Fooladi (2013) and Schoenmaker and Schramade (2018).

Galimova et al., 2022), an urgent global problem with far-reaching implications for public health and the environment. Most studies have introduced the role of technology in the economic growth-energy consumption-environmental degradation nexus. See, among others, Ozcan et al. (2020), Rahman et al. (2021), Magazzino et al. (2022), and Lasisi et al. (2022). Therefore, scholars investigated the validity of the Environmental Kuztnez Curve (EKC), an inverted U-shaped relationship between environmental degradation and economic growth. The EKC was introduced by Grossman and Krueger (1991) and several empirical applications have tested its applicability. Some authors have found the validity of EKC (*i.e.* Orubu and Omotor, 2011; Conrad and Cassar, 2014; Shahbaz et al., 2015b; Ahmad et al., 2021), while others have not validated this theory (*i.e.* Pao et al., 2011; Bakirtas and Cetin, 2017; Pontarollo and Mendieta Muñoz, 2020; Ridzuan et al., 2020). Wagner (2015) explained how the role of the cointegration relationship in the validity of the EKC is crucial to establish its validity. In addition, Mikayilov et al. (2018) discussed the concept of decoupling, understood as the growth of pollutant emissions being lower than that of GDP (relative decoupling) or, at best when the former decreases relative to economic growth (absolute decoupling).

The adoption of renewable energy brings other economic benefits: it is a generator of jobs, a catalyst for technological innovation, and a reduction in external costs related to environmental and health impacts. Several authors have studied the implications of renewable energy consumption in influencing environmental quality and economic growth. While the effectiveness of promoting renewable energy to reduce environmental degradation has been widely demonstrated, the relationship with economic growth is not clear. Although several authors (Pao and Fu, 2013; Alper and Oguz, 2016a; Kasperowicz et al., 2020; Wang et al., 2022b) have found a positive role of renewable energy on economic growth, several studies have found evidence of degrowth when renewable energy is used (Alper and Oguz, 2016b; Rommel et al., 2018; Gunderson et al., 2018; Tsagkari et al., 2021).[3]

By studying the context of energy consumption and environmental degradation, an important variable to study is temperature. The temperature of our planet is not just a matter of meteorological curiosity but is closely linked to global economic

[3] A comprehensive meta-analysis can be found in Kalimeris et al. (2014).

performance. The impacts of climate change, driven by global warming, can yield significant economic disruption, with consequences ranging from agricultural instability and supply chain disruptions to inflationary pressures and increased government spending. In fact, according to Bilgen (2014) and Martins et al. (2019), the average temperature level (and global warming more generally) affects economies, particularly the gas sector (as also demonstrated by Szoplik, 2015).

The rest of the Dissertation is organized as follows. Chapter 1 is an empirical cointegration analysis of renewable energy ETF prices, followed by an investigation of aggregate volatility and frequency spillovers. Chapter 2 attempts to explain the role of energy consumption (renewable and non-renewable) in the current economic (de)growth scenario using a new panel data technique discussed in Chudik et al. (2016). Chapter 3 concludes with a practical exploration of the role of temperature in the current energy crisis and rising inflation.

Chapter 1

Idiosyncratic and systematic spillovers through the renewable energy financial systems

Abstract

This study examines the relationship between fossil fuels energy prices and renewable energy ETFs through a two-step approach.First, we build a vector error correction model (VECM) on the daily closing prices of the commodity series from May 5, 2014 to October 31, 2023, and then use the VECM residuals to conduct a volatility spillover analysis in order to understand the behavior in mean and variance. We find evidence of cointegration among prices and a substitution (complementarity) relationship between fossil fuels and wind (solar) energy. Exploring the system's common trend and correction mechanism underscores the influential role of growing Environmental, Social, and Governance (ESG) sentiment in the market. External events, such as the Russia-Ukraine war and the Covid-19 pandemic, have discernible impacts on financial prices. The study provides valuable implications for investors and hedgers, offering guidance for portfolio optimization and emphasizing the consideration of sustainable financial products.

Keywords: Cointegration; Spillovers: Renewable Energies; Fossil Fuels; ESG.
JEL Classification: C22; C58; Q40.

1.1 Introduction

With the increasing worsening of environmental conditions, renewable energies become one of the potential solutions for improving environmental conditions. The renewable energy industry experienced rapid growth and established itself as one of the most rapidly evolving sectors within the global economy. Meanwhile, the growing "social awareness" catalyzed the transition toward more sustainable energy. Consequently, financial investors prioritize accessible options, such as green bonds or stocks, issued by environmentally responsible companies (in general, this fact is known as ESG sentiment; see, for instance Ning et al., 2022; Linhai et al., 2022).

Extensive evidence supports the notion that economic actors embracing cleaner energy production strategies, alongside a robust commitment to social responsibility, attracted substantial attention and investment from stakeholders worldwide. While social awareness played a noteworthy role in renewable energy expansion, the depletion of fossil energy sources forced economic actors to re-evaluate their development strategies, especially in light of the global impact of the Covid-19 pandemic.[1]

While a strand of literature agrees on the substitution relationship between fossil fuels and clean energies (see, Bondia et al., 2016; Barreto, 2018; Zhao, 2020), according to Karltorp and Sandén (2012), Kumar et al. (2015) and Dominioni et al. (2019) these sources could be complementary in some circumstances. Regarding substitutability, fossil energy prices play a fundamental role: their increase makes clean energy sources more attractive (see Henriques and Sadorsky, 2008; Reboredo, 2015; Bondia et al., 2016) as it stimulates investments in renewable energy, thus encouraging renewal of production systems (see, *e.g.* Sen and Ganguly, 2017; Hoang et al., 2021). Moreover, the presence of energy infrastructures, raw materials availability, and green investments determine the development of the renewable energy sector (He et al., 2019). Differently, Valckx et al. (2021) observe that a complementarity emerged when the increase in fossil energy prices led to a slowdown in energy transition mechanisms, especially after the 2015 Paris Agreement. This increase, in fact, has augmented the prices of agricultural products and raw materials on which the development of renewable plants is based to rise.

[1]Notably, on April 20th, 2020, the price of Crude Oil (WTI) fell to negative values, leading to significant challenges in global oil storage capacities.

To overcome potential limitations related to sample selection bias and inaccurate firm analysis, we employ Exchange-Traded Funds (ETFs) to capture the behavior of specific sectors. To the best of our knowledge, existing studies such as Foglia and Angelini (2020) focused on specific sectoral firms, while others like Xia et al. (2019) and Liu and Hamori (2020) used aggregate indices to explore related dynamics.

This study fills several gaps in the existing literature. From a methodological point of view, we adopt a two-step approach to study the behavior of energy prices. First, we carry out Johansen cointegration analysis to obtain the VECM residuals and secondly we use them as endogenous variables in the subsequent volatility spillover analysis based on the Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) models. From an empirical perspective, we aim to investigate the relationship between renewable and fossil energies. Specifically, we try to shed light on whether these resources are substitutes for each other, thus fostering the green transition, or whether there is a complementary relationship that keeps the current energy mix policy.

Some relevant results emerge from our empirical analysis. First, we find that energy prices are cointegrated, thus confirming the results in Bondia et al. (2016). Second, our results confirm the role of S&P500 volumes in influencing renewable energy prices as higher financial trading occurs during turbulent times. Third, focusing on volatility spillover effects, we find a short-term connection between renewable ETFs, market indices, commodities and selected fossil energy prices, with evidence of some long-term spillovers, especially during the COVID-19 pandemic. Our results are robust to the different volatility proxies we used.

The remainder of this paper is organized as follows. Section 1.2 is a brief literature review of the related works. Section 1.3 describes the dataset employed in this work and presents the theoretical framework. Section 1.4 presents and discusses the results, while section 1.5 concludes.

1.2 Literature review

The existing body of literature exploring the connections between oil prices and clean energy variables yielded intriguing insights into their spillover effects. Specifically, research on forecasting methods and spillover effects of energy stock returns has gained increasing relevance. A landmark study by Henriques and Sadorsky (2008) sets the stage for this line of inquiry by modeling the relationship between oil prices, technology stock prices, and clean energy stocks. Notably, the findings reveal that technology stock prices exert a more pronounced influence on US clean energy stock prices than oil prices, thus attributing the economic production shift toward cleaner sources and mechanisms.

Several studies, such as Kumar et al. (2012) and Managi and Okimoto (2013), further investigate the aforementioned framework, confirming the key findings presented in Henriques and Sadorsky (2008). These studies contribute to the existing literature by highlighting that, following the 2008 crisis, short-term causal relationships between macroeconomic variables and clean energy stock prices are statistically significant, with oil prices exerting a positive impact on renewable energy stock returns. Inchauspe et al. (2015) make a noteworthy contribution by employing a state-space model to examine the interconnections between the MSCI World Index, technology stock returns, and clean energy. Their research shows a high level of correlation among these variables.

The literature has extensively investigated the causal relationship between oil prices and clean energy stock returns. Using a Coupla VAR model, Reboredo (2015) finds that oil prices influence approximately 30% of the renewable energy stocks' upside and downside risk (CoVaR). Subsequently, employing a wavelet coherence analysis, Reboredo et al. (2017) examine the dependence between oil prices and renewable energy stock returns. This work reveals a weak short-term dependence that gradually strengthened in the long run, particularly during 2008-2012. In the same study, they show evidence of linear causality from oil prices to renewable energy stocks at higher frequencies, while the opposite causal direction does not hold in both the short and long term. Bondia et al. (2016) find a causal relationship through a threshold cointegration analysis, demonstrating a significant short-run relationship between oil prices and clean energy stock returns. Recently, Zhang et al. (2020), document a causal impact of oil supply and demand shocks on clean energy stocks. They employ a wavelet-based quantile-on-quantile method mixed with a Granger causality-in-quantile technique, and their results indicate a statistically significant positive effect of oil demand shocks on clean energy stocks in the medium term. Additionally, they observe an asymmetric impact of oil-specific demand shocks on higher quantiles of energy stocks in the long run.

Simultaneously, the literature examining the interactions between oil prices and renewable (or clean) energy prices has been growing, aiming to provide valuable insights for investors, opening up to hedging strategies and for policymakers in terms of policy support decisions related to renewable energy deployment. Furthermore, researchers delve into the volatility interrelationships between the oil and clean energy stock markets, commonly known as volatility spillover. Corbet et al. (2020) conduct a Dynamic Conditional Correlation Fractionally Integrated GARCH analysis, employing the original technique developed in Diebold and Yilmaz (2009), to identify the spillover effects between crude oil and renewable energies during turbulent periods, such as the fall in crude oil prices. Their findings suggest that during periods of uncertainty, investors perceive renewables as a more dependable mechanism for ensuring energy consumption demand. Volatility, in general, plays a significant role in portfolio selection strategies and the evaluation of Value-at-Risk for risk management purposes.[2] Accordingly, following Sadeghi and Shavvalpour (2006) and Wei et al. (2010), understanding the dynamics of volatility spillover is crucial in understanding the influence of clean energy stocks on oil prices and the stock market.

Using a standard OLS regression on different Realized Volatility proxies (Parkinson, 1980; Rogers and Satchell, 1991; Alizadeh et al., 2002), Dutta (2017), find that Oil Volatility Index (OVX) influence the stock market and WTI returns during both pre and post-crisis period. In addition, they show how the clean energy stock market returns are sensitive to OVX shocks. In particular, a decrease in OVX implies a reduction in clean energy realized volatility and vice-versa. On the contrary, using the revised Diebold and Yilmaz (2012) framework, Ahmad (2017) and Ferrer et al. (2018) show how technology and clean energy stocks influence the stock market returns (emits volatility spillovers), while stock market dynamics affect crude oil price (receive volatility spillovers). Ferrer et al. (2018) report a higher degree of interconnectedness during turbulent times, such as financial crises. On this line, Maghyereh

[2]See, for instance, Duffie and Pan (1997), Basak and Shapiro (2001), Jorion (2007) and many others.

et al. (2019), using a mixed wavelet GARCH method, confirms the volatility transmission between clean energy and the technology stock index. Then, Pham (2019), using the same methodology of Maghyereh et al. (2019) combined with a multivariate GARCH generalized in a Diebold and Yilmaz (2012) framework, declare how the link between oil price and clean energy prices is quite heterogeneous.

Given the corresponding literature and the increasing relevance of Environmental, Social, and Governance (ESG) products,[3] has the concern about renewables increased? How are the financial variables (co)integrated into each other? Do the innovation spillovers differ between sectors? In this work, we try to understand all these features using Exchange Traded Funds (ETF).

1.3 Empirical Analysis

This paper aims to investigate two distinct aspects. First, we analyze the relationship between renewable energies, fossil fuels, and commodity prices. Through a cointegration analysis sought to spot the error correction mechanism in the series, we aim to investigate the economic behavior of the different sectors. Second, we use the VECM residuals to conduct a spillover analysis based on volatilities' proxies.

1.3.1 The Data

The data refers to the daily time series of 6 commodity prices and 4 energy Exchange-Traded Funds (ETF) over a period from May 5, 2014, to October 31, 2023 ($T = 2478$ observations). The source is the Yahoo Finance database.[4] The start date depends on data availability, thus allowing us to study the period following the Paris Agreement (2015), the most recent international treaty on climate change. This agreement aims to develop capital flows into sustainable businesses, renewable energy initiatives, and low-carbon innovations by limiting polluting emissions, requiring transparent behavior and environmentally responsible practices from companies. All time series are plotted in Figure 1.1.

[3] For a general review of ESG investments at firm level see Gillan et al. (2021).

[4] The Yahoo finance database is a free accessible storage of financial market data.

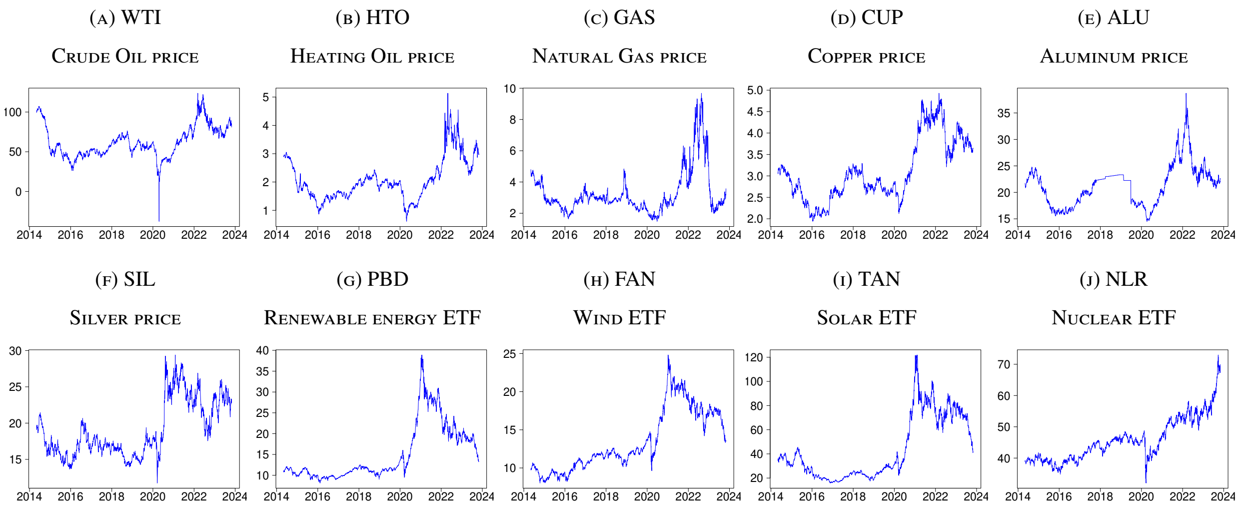


Figure 1.1: Closing Prices

Since the prices of renewable energies are not available on the stock markets, we employ ETFs for renewable energies because of their ability to replicate the specific market/sector indexes. Therefore, we use Invesco Solar (TAN), First Trust Global Wind Energy (FAN), and VanEck Vector Uranium+Nuclear Energy (NLR)[5] representing the solar, wind and nuclear energy markets. We also use the Invesco Global Clean Energy ETF (PBD), which takes into account the temporal evolution of an aggregate of renewable energies by replicating the WilderHill New Energy Global Innovation Index. This inclusion contributes to the robustness of our results.

To improve the readability, Table 1.1 provides a concise overview of the characteristics of the ETFs. Numerous energy ETFs and indices have emerged in financial markets, including offerings from BlackRock and iShares. While the time series behavior of these options is similar, we opted for ETFs based on data availability, not performance, since our work is not a pure portfolio optimization investigation nor a specific hedging analysis because it aims to provide general insights.

Given our dataset, we investigate the contagion effects between renewable energies and fossil fuels using the Crude Oil West Texas Intermediate (WTI).[6] The increasing awareness surrounding sustainable production methods has prompted many companies, especially those listed on the stock market, to reassess their manufacturing

[5] Disclaimer: even though we know that nuclear energy is not renewable, we consider it renewables but it is (clearly) clean (it does not pollute).

[6] Given the negative value reached by the WTI on April 20th, 2020, we cannot include the log of prices in our analysis.

Ticker	ETF	Sector	Description
PBD	Invesco Global Clean Energy	Renewables	The investment objective of the Fund is to achieve the net total return performance of the WilderHill New Energy Global Innovation Index less fees, expenses and transaction costs
TAN	Invesco Solar	Solar energy	It is based on the MAC Global Solar Energy Index. It is computed using the net return and are rebalanced quarterly
FAN	First Trust Global Wind Energy ETF	Wind energy	The investment objective of the Fund is to seek investment results that correspond generally to the price and yield, before the Fund's fees and expenses, of an equity index called the ISE Clean Edge Global Wind Energy Index
NLR	VanEck Vectors Uranium & Nuclear Energy	Nuclear energy	It seeks to replicate as closely as possible, before fees and expenses, the price and yield performance of the MVIS Global Uranium & Nuclear Energy Index (MVNLRTR)

Table 1.1: Renewable EFTs

processes. Consequently, this transition has amplified the interest of global investors in renewable and clean energies. To deepen our analysis, we also consider the price of Natural Gas (NG) and Heating Oil (HO), which have been the subject of extensive discussion since the onset of the Russia-Ukraine war, that has produced several issues in financial markets due to the sudden energy supply interruption.

The energy crisis had significant consequences on financial markets, including the rise in raw material prices. To examine the interactions between these factors and energy components, both renewable and non-renewable, we incorporate the prices of copper, silver, and aluminum. We do not include gold price in this analysis due to the singular characteristics of this metal, such as storage of value and hedging risk properties. In addition, gold is not used for the production processes of renewable energy plants, while copper, silver, and aluminum are relevant in this sense. The increase in functional raw materials prices can negatively affect the energy transition.

The results of the Unit Root tests reported in Table 1.2 confirm that the prices are non-stationary. In standard energy finance applications, it is traditional to work with stationary series, employing returns obtained through the first logarithmic difference. However, since our primary focus is on the long-run average influence among the variables, we prefer to keep the original closing prices without differencing them and losing information.

In this study, we include $n = 4$ additional control variables (exogenous), which account for market sentiment. We incorporate the exchange volumes of two major financial indices: the SP500, representing the American market, and the STOXX50,

	WTI	PBD	FAN	TAN	NLR	NG	COP	SIL	ALU	HO
Mean	62.2664	15.1731	45.7074	43.588	13.4714	3.2724	3.1038	19.0432	21.355	2.0752
Med.	58.36	11.6886	44.7814	31.2805	11.9316	2.84	2.93	17.567	21.9787	1.9284
SD	19.7193	6.7061	6.9192	25.8306	3.9676	1.4215	0.7125	3.8444	3.8791	0.736
Max	123.7	38.9014	72.99	121.94	24.8175	9.68	4.929	29.398	38.73	5.1354
Min	-37.63	8.1284	32.0036	15.8312	8.0181	1.482	1.9395	11.735	14.52	0.6104
Kurt.	3.2143	3.8148	3.7786	2.4314	2.3001	7.6857	2.3869	2.2113	4.2352	3.7392
Skew.	0.5463	1.3096	0.9559	0.8486	0.6891	2.1091	0.6164	0.6696	0.7892	0.9817
ADF	−3.1134	−1.5587	−1.9414	−1.7566	−1.6132	−2.8088	−2.453	−3.2669	−1.9694	−2.6619
	(0.107)	(0.7651)	(0.6031)	(0.6814)	(0.7421)	(0.2359)	(0.3865)	(0.0764)	(0.5913)	(0.2981)
PP	−12.8773	−4.2459	−15.7969	−6.0807	−7.0639	−15.0104	−9.7736	−18.2136	−8.3966	−11.8999
	(0.3915)	(0.8729)	(0.2287)	(0.7706)	(0.7157)	(0.2725)	(0.5646)	(0.0984)	(0.6414)	(0.446)
KPSS	5.874	15.904	20.6344	16.9546	21.0726	4.2765	15.9037	13.7977	6.6203	8.2097
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)

Note: p-values in parenthesis (KPSS test pvalues are higher than 0.01). The unit roots (the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS)) tests are conducted selecting the lag with the lowest AIC and with a constant and trend specification of the deterministic component.

Table 1.2: Descriptive Statistics and unit root tests

representing the European market; which are known to be well suited to capturing volatility dynamics or financial bubbles.

Additionally, we include two dummy variables, namely the "Covid-19 period" and the "Russia-Ukraine conflict", to account for their respective impacts on the economic environment. The "Covid-19 period" dummy corresponds to the recessionary period caused by the Covid-19 pandemic, as identified by the National Bureau of Economic Research (NBER), February-April 2020.[7] On the other hand, the "Russia-Ukraine conflict" dummy captures the effects and consequences of the Ukrainian-Russian conflict, starting from its outbreak (February 25th, 2022) to the end of the sample.

However, since several specific events occurred, we incorporate some specific-date dummies, such as:

- April 20 and 21, 2020: the unprecedented fall of oil prices into negative territory for transport limitations;
- March 9 and 16, 2020: the sharp decline in commodity prices attributed to the Covid-19 pandemic;
- February 18th and June 27th, 2018: two severe spikes observed in aluminum (and copper) prices.

[7] We did several trials for the setting of the Covid-19 dummy around the February-April 2020 period with robust results.

1.3.2 Methodology

We develop a cointegration analysis followed by a standard spillover analysis on the squared VECM residuals. Accordingly, we used the Johansen procedure to allow for testing the validity of some hypotheses on the cointegration matrix.

The methodology employed can be summarized in different steps:

- First, we employ the Johansen cointegration method, which allows hypothesis testing on the cointegrating vector, thereby enabling the investigation of the common factors influencing prices.[8]

- Second, we use squared residuals from the VECM model as a consistent measure of realized volatility in a standard VAR analysis.[9]

- Third, we conduct a spillover analysis based on the Diebold and Yilmaz (2012); Diebold and Yılmaz (2014) (DY) and Baruník and Křehlík (2018) (BK) methodology.

Despite a large literature on financial contagion and spillover,[10] there is no universally accepted definition of it. According to Forbes and Rigobon (2002), the spillover is the significant increase in cross-market linkages after a shock to one market (or group of markets). In particular, we consider volatility spillovers following Liu and Hamori (2020), who defined the spillover as the "contagion effect" that occurred after sudden changes in the series behavior.

Cointegration analysis

The non-stationarity of the time series raises the cointegration problem, which we address using the Johansen (1991) technique. The Johansen technique defines five different specifications of the deterministic component:

- case 1: no constant;

[8]We do not employ a first step based on GARCH conditional volatility proxy since the estimation relies on a fitted regressor, which introduces inherent biases and measurement errors in the spillover analysis.

[9]See, for instance,Andersen et al. (2003); Andersen and Benzoni (2008); Andersen and Teräsvirta (2009).

[10]See, for instance, King et al. (1990), Susmel and Engle (1994), Allen and Gale (2004), Longstaff (2010) and many others.

- case 2: restricted constant;
- case 3: unrestricted constant;
- case 4: constant + restricted trend;
- case 5: constant + unrestricted trend.

Several similarities emerged from Figure 1.1. Notably, the entire dataset shows an upward trend, particularly after the onset of the Covid-19 outbreak. Since cases 1 and 2 are not applicable in this context, we test cases 3, 4, and 5, which agree on the existence of 3 cointegration vectors. Specifically, given the slightly positive exponential trend of renewable energy ETFs, we proceed with case number 5, the least restrictive possible.

Table 1.3 presents the Trace and λ-max results for the constant and the unrestricted trend with the number of lags equal 2 according to the minimization of the Bayesian Information Criteria (BIC).[11] Although the tests disagree, we follow Kasa (1992) and Serletis and King (1997) in arguing that the Trace test has greater power than the λ-max statistic, concluding that the cointegration rank is 3. In addition, once we put all the series together as in Figure 1.2, it is evident how 1 cointegrating trend is not admissible in this context while 3 is a plausible number.

Rank	Eigenvalue	Trace test	λ-max test
0	0.0332	319.20 (0.0000)	82.718 (0.0005)
1	0.0242	236.48 (0.0027)	**59.937 (0.0720)**
2	0.0173	176.54 (0.0412)	42.753 (0.5278)
3	0.0148	**133.79 (0.0990)**	36.566 (0.5651)
4	0.0119	97.223 (0.1912)	29.452 (0.6666)
5	0.0103	67.771 (0.2715)	25.455 (0.5662)
6	0.0068	42.316 (0.4102)	16.409 (0.8174)
7	0.0059	25.907 (0.3393)	14.626 (0.5461)
8	0.0043	11.282 (0.3722)	10.781 (0.3354)
9	0.0002	0.50088 (0.4791)	0.50088 (0.4791)

p-value in parenthesis

Table 1.3: Trace and λ-max tests

Following this preliminary part, we estimate a Vector Error Correction Model (VECM)

$$\Delta \boldsymbol{y}_t = \boldsymbol{c}_t + \Pi \boldsymbol{y}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta \boldsymbol{y}_{t-i} + \mathcal{B}\boldsymbol{Exo}_t + \boldsymbol{\zeta}_t, \tag{1.1}$$

[11] Statistics for cases n.3 and 4 are available upon request.

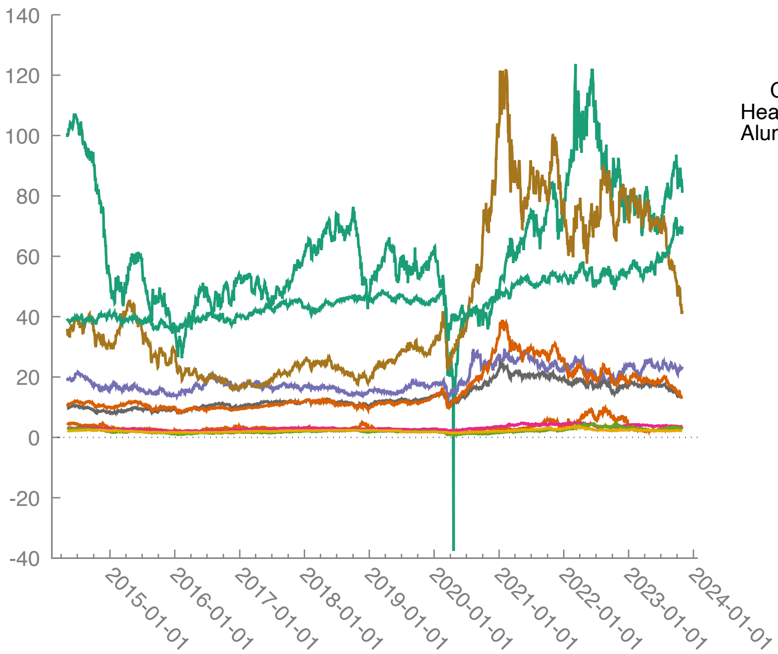


Figure 1.2: Closing Prices in a single chart

where $\boldsymbol{y}_t$ is a 10-dimensional vector of endogenous variables, $p = 2$ is the lag order according to the minimization of the BIC Information Criteria, Π is the matrix of long run coefficients, Γ_i are matrices of short-run coefficients, $\mathcal{B}$ is the estimated matrix coefficient for the exogenous variables and $\boldsymbol{Exo}_t$ is the vector of exogenous regressors, and $\boldsymbol{\zeta}$ is the error component. In addition, given the trend identification discussed, $\boldsymbol{c}_t = \mu_o + \mu_1 t$. Therefore, since the rank ($r = 3$) of Π matrix is lower than n (full rank) and higher than 0, Π can be written as $\alpha\beta'$ and the VECM equation can be identified as

$$\Delta \boldsymbol{y}_t = \mu_0 + \mu_1 t + \alpha\beta' \boldsymbol{y}_{t-1} + \Gamma \Delta \boldsymbol{y}_{t-1} + \mathcal{B}\boldsymbol{Exo}_t + \boldsymbol{\zeta}_t \tag{1.2}$$

where β is estimated to guarantee that $\beta' \boldsymbol{y}_t$ is a stationary process.

Diebold and Yilmaz (2009)

Following the cointegration analysis, we develop a spillover section based on the Diebold and Yilmaz (2012) procedure. Some empirical works, such as Nazlioglu et al. (2013), Liu and Hamori (2020) and Dahl et al. (2020), employ the estimated conditional variances from a GARCH model as input for the VAR framework, which allows the investigation of the spillover between the series. However, this procedure suffers from the generated regressors problem that basically leads to smaller standard error since generated regressors have their own sample variance. Therefore, we build the Diebold and Yilmaz (2012) methodology on the time series of errors (ζ_t) obtained from the estimation of the VECM system in Equation (1.2). We aim to understand the role of volatility spillovers between the series. We partially follow the spillover definition from Forbes and Rigobon (2002), where for each innovation i, the spillover index adds the shares of its own forecast error variance coming from shocks to asset j.

The original Diebold and Yilmaz (2009) procedure, follows the estimation of a standard VAR system on stationary variables. For example, let consider the standard bivariate VAR(1) model

$$\boldsymbol{z}_t = \boldsymbol{d}_t^* + \Phi \boldsymbol{z}_{t-1} + \boldsymbol{\nu}_t \tag{1.3}$$

where $\boldsymbol{d}_t^*$ is the deterministic component, Φ is the matrix of parameters, $\boldsymbol{\nu}_t$ is the error term, and $\boldsymbol{z}_t$ is a vector made by the two series.[12] Since the Diebold and Yilmaz (2009) methodology is often used in financial economic series, such as returns, the average value is zero, leading to assume the deterministic component is null. Therefore, we do not consider $\boldsymbol{d}_t^*$. The process is assumed to be covariance stationary, so it is possible to obtain a Moving Average (MA) representation of the VAR as follows

$$\boldsymbol{z}_t = \boldsymbol{\Theta}(L)\boldsymbol{\nu}_t, \quad \text{with} \quad \boldsymbol{\Theta}(L) = (\boldsymbol{I}_2 - \boldsymbol{\Phi}L)^{-1}. \tag{1.4}$$

where $\mathbf{I}_2$ is the identity matrix. Using the Cholesky transformation it can be useful to rewrite the Equation (1.4) as

$$\boldsymbol{z}_t = \boldsymbol{A}(L)\boldsymbol{u}_t, \tag{1.5}$$

with $\boldsymbol{A}(L) = \boldsymbol{\Theta}(L)\boldsymbol{Q}^{-1}$, $\boldsymbol{u}_t = \boldsymbol{Q}\boldsymbol{\nu}_t$, $\mathrm{E}(\boldsymbol{u}_t\boldsymbol{u}_t') = \boldsymbol{I}_2$, with $\mathbf{Q}$ is the lower triangular Cholesky factor of the covariance of $\boldsymbol{\nu}_t$. The optimal one-step ahead forecast is

$$\boldsymbol{z}_{t+1} = \Phi \boldsymbol{z}_t \tag{1.6}$$

[12] In general financial applications, $\boldsymbol{z}_t$ is a vector of n stock returns or volatilities.

and the following one-step ahead error vector ($\boldsymbol{u}_{t+1}$) is:

$$\boldsymbol{u}_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix} \quad \text{where} \quad \mathrm{E}(\boldsymbol{u}_{t+1}\boldsymbol{u}'_{t+1}) = \boldsymbol{A_0}\boldsymbol{A'_0}, \tag{1.7}$$

is the covariance matrix. This formulation comes from the initial hypothesis of two series in the VAR that can be generalized to n factors. For the first series ($x_{1,t}$) the one-step ahead error in forecasting is $a^2_{0,11} + a^2_{0,12}$, while for the second it is $a^2_{0,21} + a^2_{0,22}$. This variance decomposition allows us to split the forecast error variances of each variable into different parts: the percentage of the one-step ahead error variance in forecasting x_1 is due to shocks to x_1 (this is called *own variance shares*), and for shocks to x_2 (this is called *cross variance shares*). Broadly, we are discussing the Impulse Response Function (IRF) method to understand the dynamic behavior of the system when a shock occurs.

There exist two possible spillovers in our example with two variables: x_{1t} shock that affects the forecast error variance of x_{2t} (with contribution $a^2_{0,21}$) and x_{2t} shock that affects the forecast error variance of x_{1t} (with contribution $a^2_{0,12}$). The sum of their contributions gives the total spillover: $a^2_{0,12} + a^2_{0,21}$. Consequently, the percentage ratio between the total spillover and total forecast error variation gives the (bivariate) Spillover index is given by the total forecast error variation (the sum of all components in $\boldsymbol{A}_0$):

$$\boldsymbol{BiS} = \frac{a^2_{0,12} + a^2_{0,21}}{a^2_{0,12} + a^2_{0,21} + a^2_{0,11} + a^2_{0,22}} \tag{1.8}$$

Obviously, this index can be generalized to p^{th}-order n-variable VAR (still with a one-step ahead forecast) and can be more elegantly reported in matrix form for h steps:

$$\boldsymbol{BiS}_h = \sum_h \frac{\boldsymbol{\iota}'\boldsymbol{A}_h\boldsymbol{A}'_h\boldsymbol{\iota} - \mathrm{tr}(\boldsymbol{A}_h\boldsymbol{A}'_h)}{\boldsymbol{\iota}'\boldsymbol{A}_h\boldsymbol{A}'_h\boldsymbol{\iota}}. \tag{1.9}$$

where $\mathrm{tr}()$ is the trace operator and ι is the vector of ones. However, the Diebold and Yilmaz (2009) framework has a few limitations, methodological and empirical. First, the spillover index refers to the Cholesky-factor identification of the VAR, which makes the resulting error variance decomposition dependent on variable ordering. Second, the spillover index measures the total spillovers, not the directional ones, which are more interesting to analyze. The first issue is fixed by the Generalized Vector AutoRegressive (GVAR) system introduced by Koop et al. (1996) and Pesaran and Shin (1998) (KPPS). The second one is addressed implementing the net spillover which clarify the direction of spillovers from a series to another.

Diebold and Yilmaz (2012)

The Diebold and Yilmaz (2012) methodology fixed the issues in Diebold and Yilmaz (2009). Let generalize Equation (1.3) setting the determinstic component to zero and considering the VAR in companion form

$$\boldsymbol{x}_t = \boldsymbol{\Phi}\boldsymbol{x}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{1.10}$$

with $\boldsymbol{\varepsilon}_t \sim WN(\mathbf{0}, \boldsymbol{\Sigma})$. As in Equation (1.5) let us consider a Moving Average (MA) representation

$$\boldsymbol{x}_t = \sum_{i=0}^{\infty} \boldsymbol{\Psi}_i \boldsymbol{\varepsilon}_{t-i}, \tag{1.11}$$

with $\boldsymbol{\Psi}_0 = \boldsymbol{I}_n$. The MA representation leads to the Impulse Response Function (IRF) and the Forecast Error Variance Decomposition (FEVD). As we noted, the FEVD makes it possible to split the influence of the shocks. The standard VAR representation uses the Cholesky factorization based on the orthogonality property of innovations. Economically, it identifies the shock as independent of others. On the contrary, the Generalized VAR (GVAR) allows possible correlated shocks but calculates them appropriately, using the historically observed distribution of errors. Therefore, since shocks are not orthogonalized, the sum of the single contributions to the variance error forecast is not necessarily equal to one, as for the standard VAR.

Denoting with $\theta^g_{i,j}(H)$ the KPPS H-step ahead forecast error variance decomposition (FEVD), we obtain

$$\theta^g_{i,j}(H) = \sigma_{jj}^{-1} \sum_{h=0}^{H-1} \frac{(\boldsymbol{\epsilon}_i' \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \boldsymbol{\epsilon}_j)^2}{(\boldsymbol{\epsilon}_j' \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \boldsymbol{\Psi}_h' \boldsymbol{\epsilon}_i)}, \tag{1.12}$$

where $\boldsymbol{\Sigma}$ is the covariance matrix for the vector $\boldsymbol{\varepsilon}_t$, σ_{jj} is the standard deviation of the error term for the j-th equation and $\boldsymbol{\epsilon}$ is the *selection vector* with 1 as the i-th element and 0 otherwise. The sum of $\theta^g_{ij}(H)$ is not equal to 1 since the shocks are not orthogonalized and, to use all the necessary information available in the variance decomposition matrix for the calculation of the spillover index, each entry of $\theta^g_{ij}(H)$ must be normalized

$$\tilde{\theta}^g_{i,j}(H) = \frac{\theta^g_{i,j}(H)}{\boldsymbol{\iota}'\boldsymbol{\theta}^g(H)\boldsymbol{\iota}}. \tag{1.13}$$

The Total Spillover Index (TSI), measured with the GVAR framework is

$$\boldsymbol{TSI}^g(H) = \frac{\boldsymbol{\iota}'\tilde{\boldsymbol{\theta}}^g(H)\boldsymbol{\iota} - \mathrm{tr}(\tilde{\boldsymbol{\theta}}^g(H))}{\boldsymbol{\iota}'\boldsymbol{\theta}^g(H)\boldsymbol{\iota} - 1} \tag{1.14}$$

The TSI measures the contribution of spillovers from a volatility shock across asset classes to the total forecast error variance. The Generalized VAR approach, invariant for the variable ordering, allows us to learn more about the direction of the volatility spillover across the class assets. The direction volatility spillover received by market i from all other markets j is measured as

$$\begin{aligned} \boldsymbol{S}^g_{i.}(H) &= \frac{1}{n}\left[\boldsymbol{\iota}'\tilde{\boldsymbol{\theta}}^g_{i,j}(H)\boldsymbol{\iota} - \mathrm{tr}(\tilde{\boldsymbol{\theta}}^g_{i,j}(H))\right] \\ \boldsymbol{S}^g_{.i}(H) &= \frac{1}{n}\left[\boldsymbol{\iota}'\tilde{\boldsymbol{\theta}}^g_{j,i}(H)\boldsymbol{\iota} - \mathrm{tr}(\tilde{\boldsymbol{\theta}}^g_{j,i}(H))\right] \end{aligned} \tag{1.15}$$

Then the *net volatility spillover* from market i to all other markets j is computed as

$$\boldsymbol{S}^g_{i}(H) = \boldsymbol{S}^g_{.i}(H) - \boldsymbol{S}^g_{i.}(H). \tag{1.16}$$

The net volatility spillover is the difference between the gross volatility shocks transmitted to the other markets and the received. To conclude, the *net pairwise volatility spillovers* between markets i and j can also be calculated as a simple difference between the gross volatility shocks transmitted from market i to market j and those transmitted from j to i

$$\boldsymbol{S}^g_{i,j}(H) = \frac{1}{n}\left[\boldsymbol{\iota}'\tilde{\boldsymbol{\theta}}^g_{i,j}(H)\boldsymbol{\iota} - \boldsymbol{\iota}'\tilde{\boldsymbol{\theta}}^g_{j,i}(H)\boldsymbol{\iota}\right]. \tag{1.17}$$

This pairwise comparison determines the prevalence of volatility spillovers between series. If it is positive, it means that spillover from series/market i exhibits a higher degree of turbulence on another j (and vice-versa).

Baruník and Křehlík (2018)

Since the economic literature has recognized the importance of persistence in financial analysis, using spectral methods such as Baruník and Křehlík (2018) (BK), we can emphasize the duration of spillovers, not identifiable by the DY method. The BK framework is based on the Generalized Forecast Error Variance Decomposition (GFEVD) as expressed in Eq. (1.12), dealing with the frequency domain. Denoting with $\boldsymbol{\Psi}$ the VMA matrix coeffcients in Equation (1.11) this method explores the spectral behavior of each independent variable by employing its own frequency response function

$$\boldsymbol{R}_x(\omega) = \sum_{h=-\infty}^{\infty} E(\boldsymbol{x}_t \boldsymbol{x}'_{t-h}) e^{-i\omega h} = \Psi(e^{-i\omega}) \boldsymbol{\Sigma} \Psi'(e^{i\omega}), \tag{1.18}$$

where $\Psi(e^{-i\omega}) = \sum_h (e^{-i\omega h}) \Psi_h$ is obtained as a Fourier transformation of the coefficients Ψ_h with $i = \sqrt{-1}$, $\boldsymbol{\Sigma}$ is the covariance matrix for error terms in Eq. (1.11) and $\boldsymbol{x}_t$ is the vector of endogenous variables in the VAR model in Eq. (1.10). The power spectrum $\boldsymbol{R}_x(\omega)$ is a fundamental quantity for understanding frequency dynamics since it describes how the variance of $\boldsymbol{x}_t$ is distributed over the frequency components ω.

Using the spectral representation for covariance,[13] the frequency domain counterparts of variance decomposition emerged. Denoting with k and j the considered series,the spectral GFEVD on the ω frequency is expressed as

$$\mathbb{F}(\omega)_{k,j} = \sigma_{jj}^{-1} \frac{|(\Psi(e^{-i\omega})\boldsymbol{\Sigma})_{k,j}|^2}{[\Psi(e^{-i\omega})\boldsymbol{\Sigma}\Psi'(e^{-i\omega})]_{k,k}} \tag{1.19}$$

where $\Psi'(e^{-i\omega})$ is the Fourier transformation of the Impulse Response Ψ_h. It is important to note that $\mathbb{F}(\omega)_{k,j}$ represents the spectrum of the j-th variable at a given ω frequency in the k-th variable (for the sake of simplicity we do not use the index i which, for the spectral decomposition, refers to the complex root). The natural economic interpretation of this quantity is within frequency causation as the denominator holds the spectrum of the jth variable at a given frequency ω.

Since we are working with unconditional GFEVD, the forecast horizon does not

[13] $E(\boldsymbol{x}_t \boldsymbol{x}'_{t-h}) = \int_{-\infty}^{\infty} \boldsymbol{R}_x(\omega) e^{i\omega h} d\omega$

play a relevant role, considering infinite horizon relations. Given an arbitrary frequency band $d = (a, b)$, with $a, b \in (-\pi; \pi)$, the Generalized Variance Decompositions on frequency band d ($\boldsymbol{\Theta}_d$) are defined as:

$$(\boldsymbol{\Theta}_d)_{k,j} = \frac{1}{2\pi}\int_a^b \boldsymbol{\Gamma}_k(\omega)\mathbb{F}(\omega)_{k,j}d\omega \tag{1.20}$$

$$\text{where} \quad \boldsymbol{\Gamma}_k = 2\pi\frac{[\boldsymbol{\Psi}(e^{-i\omega})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(e^{-i\omega})]_{k,k}}{\int_{-\pi}^{\pi}[\boldsymbol{\Psi}(e^{-i\lambda})\boldsymbol{\Sigma}\boldsymbol{\Psi}'(e^{-i\lambda})]_{k,k}\,d\lambda}$$

is a weighting function that represents the power of the jth variable at a given frequency, where λ is the subsequent frequency and sums over frequencies to a constant value of 2π. The generalized causation spectrum is the squared modulus of the weighted complex numbers, thus producing a real quantity. The scaled generalized variance decomposition on the frequency band d is:

$$(\tilde{\boldsymbol{\Theta}}_d)_{k,j} = \frac{(\boldsymbol{\Theta}_d)_{k,j}}{\sum_j(\boldsymbol{\Theta}_\infty)_{k,j}} \quad \text{with} \quad (\boldsymbol{\Theta}_\infty)_{k,j} = \frac{1}{2\pi}\int_{-\pi}^{\pi}\boldsymbol{\Gamma}_k(\omega)\mathbb{F}(\omega)_{k,j}d\omega. \tag{1.21}$$

Subsequently, inspired by the DY spillover measures on the GFEVD, we can define the frequency domain spillovers. According to Eq. (1.21), the overall spillover on frequency band d is:

$$\boldsymbol{S}_d^W = 100\left[1 - \frac{\text{tr}((\tilde{\boldsymbol{\Theta}}_d)_{k,j})}{\boldsymbol{\iota}'(\tilde{\boldsymbol{\Theta}}_d)_{k,j}\boldsymbol{\iota}}\right] \tag{1.22}$$

When the value of S_d^W is high (more than 80%), it indicates a massive spillover effect within the respective frequency band not related to the aggregate spillover measure, which might be relatively low. For this reason, we set the apex W to indicate the within spillover. Despite the spillover, the contribution of a given frequency band d to the aggregate measure may be of more interest. This can be proved by weighing the within measure. The aggregate measure on the frequency band d is then defined as frequency spillover:

$$\boldsymbol{S}_d^F = \boldsymbol{S}_d^W\left[\frac{\boldsymbol{\iota}'(\tilde{\boldsymbol{\Theta}}_d)_{k,j}\boldsymbol{\iota}}{\boldsymbol{\iota}'(\tilde{\boldsymbol{\Theta}}_\infty)_{k,j}\boldsymbol{\iota}}\right] \tag{1.23}$$

The sum of S_d^F equals the total connectedness exploited in Eq. (1.14). The degree of decomposition can be decided by accounting for long and short movements.

1.4 Results

1.4.1 Cointegration analysis

Since we employed the Johansen technique for the statistical inference allowed, we do not report the verbose unrestricted VECM preliminary results,[14] but in Table 1.4 we show the corresponding cointegration vector β. Given the significant daily closing price observations ($T = 2478$), the inference on the cointegration vector β can be considered robust. Testing for some patterns in β ensures the accuracy of the estimated long-run relationship estimation between variables. Based on the results of Table 1.4, we test the following 8 restrictions including the indetification constraints:

	β_1	β_2	β_3
WTI	1.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
PBD	0.0000	1.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Copper	0.0000	0.0000	1.0000
	(0.0000)	(0.0000)	(0.0000)
FAN	0.1465	-1.6596	-0.298
	(0.809)	(0.1615)	(0.0541)
TAN	0.0067	-0.1037	0.0145
	(0.0721)	(0.0144)	(0.0048)
NLR	0.889	-0.4713	-0.0642
	(0.2527)	(0.0504)	(0.0169)
NG	3.1021	-0.357	0.0777
	(0.7355)	(0.1469)	(0.0492)
Silver	-1.1418	0.2051	-0.0065
	(0.356)	(0.0711)	(0.0238)
Aluminium	1.5179	2.666	-0.9754
	(2.7908)	(0.5573)	(0.1868)
HeatingOil	-37.750	-0.4052	0.0109
	(2.1634)	(0.4320)	(0.1448)

standard errors in parenthesis

Table 1.4: Unrestricted VECM cointegration vector estimation

- the influence of renewable energies ETFs (TAN, FAN, NLR) in the first cointegrating relationship is nul (3 constraints, PBD: identification);
- the copper price in the second cointegration vector is zero (identification 1 constraint);

[14] The unrestricted estimations are available upon request.

- the impact of fossil fuels (Crude Oil, Natural Gas and Heating Oil) in the second and third cointegration vector is zero (3 constraints, WTI: identification);
- the silver price is not relevant for the third cointegration vector (1 constraint).

The LR test is given in the table 1.5. Since we cannot reject the restrictions, we estimate the restricted model in Eq. (1.2). Table 1.6 shows the corresponding restricted VECM cointegration vectors while Table 1.7 reports the results.

Unrestricted loglikelihood (l_u)	8384.0451
Restricted loglikelihood (l_r)	8376.7252
$2\,(l_u - l_r)$	14.6398
$P(\chi^2(8) > 14.6398)$	0.0665

Table 1.5: LR test on VECM

As expected, the Covid-19 dummy reduces crude oil prices. However, it does not affect renewable energy and commodities, except aluminum, as reported by Mehta et al. (2022). This result is due to the drop in oil prices during the pandemic, thus indicating that the renewable energy market did not feel the crisis like fossil fuels. In particular, the sudden outage of transportation causes a decrease in fossil prices.

	β_1	β_2	β_3
WTI	1.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
PBD	0.0000	1.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)
Copper	0.0000	0.0000	1.0000
	(0.0000)	(0.0000)	(0.0000)
FAN	0.0000	-1.6284	-0.4074
	(0.0000)	(0.1220)	(0.0662)
TAN	0.0000	-0.1142	0.0255
	(0.0000)	(0.0112)	(0.0071)
NLR	0.0000	-0.3319	-0.1381
	(0.0000)	(0.0380)	(0.0239)
NG	1.8545	0.0000	0.0000
	(0.5954)	(0.0000)	(0.0000)
Silver	-1.0552	0.2466	0.0000
	(0.2019)	(0.0537)	(0.0000)
Aluminium	6.8407	1.5957	-0.8791
	(2.4126)	(0.3547)	(0.2107)
HeatingOil	-39.681	0.0000	0.0000
	(1.8581)	(0.0000)	(0.0000)

Table 1.6: Restricted VECM cointegration vector estimation

In contrast, the effect of the Russia-Ukraine conflict is significant for wind, solar, and nuclear energies, with the highest magnitude reached by solar energy. During the war, the supply crisis drove up fossil energy prices except Crude Oil. As a result, especially economies with a high dependence on Russian supplies (*e.g.*, Europe), tried to immediately convert energy consumption more sustainably, thus also causing prices to rise due to the lack of infrastructure for this transition.

In general, SP500 trading volumes reduce the price of listed stocks. In particular, higher trading volumes reduce the quotation of renewable energy ETFs. Since ETFs reflect the performance of companies operating in such sectors, wind, solar, and nuclear energy companies' performances decrease as financial trading volumes increase. The increase in financial swaps occurs during the period of higher volatility, which means that the overall level of uncertainty in the market is pronounced. As a result, the renewable energy market suffers from increased market uncertainty. These considerations do not apply to European investors, as they have less influence on the price of energy stocks, underlining the crucial role of the US market in influencing the performance of renewable energy companies.

Since we employ ETFs, the increase in prices means that the value of the companies associated with the index increases (this is not an increase in the price of renewables). Therefore, the growing value of renewable companies is associated with the increasing interest in renewable energies. Crude oil, heating oil, and natural gas do not impact ETFs, confirming Reboredo (2015) and Sun et al. (2019).

While the average renewable energy ETF (PBD) does not significantly impact crude oil prices, solar (TAN) and wind (FAN) ETFs influence WTI. An increase in the wind market (FAN) performance generates a decrease in WTI price by 0.479 points, indicating a substitution relationship between wind energy and crude oil, consistent with findings by Dominioni et al. (2019). To be more accurate, the increased performance of the wind sector could shift investor interest towards this renewable energy sector. The growth and progress of the wind sector could improve the technology and infrastructure used, reducing the costs of using wind energy. The contraction in the cost of wind energy inevitably leads to its use (consumption and production) growing. Therefore, the demand market function for crude oil decreases, reducing the corresponding equilibrium price.

Interestingly, an increase in TAN corresponds to a rise of 0.1365 points in the price of WTI, supporting the Dominioni et al. (2019) claim about the complementary

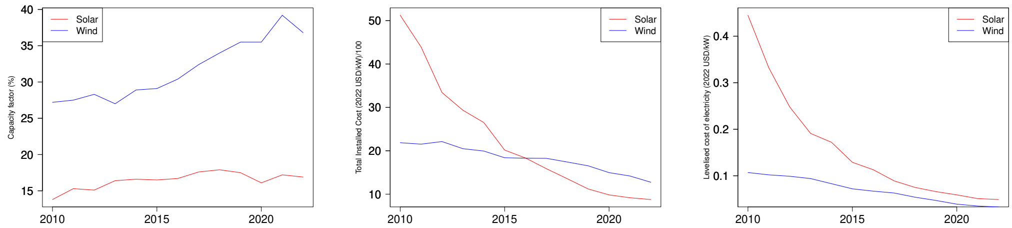
	Δ Crude Oil	Δ Renewables	Δ Copper	Δ Wind	Δ Solar	Δ Nuclear	Δ Natural Gas	Δ Silver	Δ Aluminium	Δ HO
Const	0.2994 (0.5649)	0.5999 *** (0.1114)	0.0067 (0.0166)	0.6491 *** (0.0661)	2.0346 *** (0.5002)	1.4360 *** (0.1764)	0.0367 (0.0585)	0.3793 *** (0.1325)	−0.0063 (0.0099)	0.0456 ** (0.0205)
Δ WTI_{t-1}	−0.0007 (0.0202)	0.0041 (0.0040)	0.0002 (0.0006)	0.0007 (0.0024)	0.0159 (0.0179)	−0.0075 (0.0063)	0.0006 (0.0021)	0.0064 * (0.0047)	−0.0003 (0.0004)	−0.0021 *** (0.0007)
Δ PBD_{t-1}	0.0563 (0.2457)	−0.2513 *** (0.0485)	0.0209 *** (0.0072)	−0.0853 *** (0.0287)	−0.8796 *** (0.2175)	−0.0915 (0.0767)	0.0172 (0.0254)	−0.0333 (0.0576)	0.0050 (0.0043)	−0.0119 * (0.0089)
Δ Cop_{t-1}	0.0949 (0.8243)	−0.2957 ** (0.1626)	−0.0487 ** (0.0242)	−0.0872 (0.0964)	−1.3061 ** (0.7298)	−0.2423 (0.2574)	−0.0046 (0.0854)	−0.0251 (0.1934)	0.0112 (0.0144)	0.0315 (0.0299)
Δ FAN_{t-1}	−0.4790 ** (0.2910)	0.2058 *** (0.0574)	−0.0195 ** (0.0085)	0.0150 (0.0340)	0.7931 *** (0.2576)	0.0477 (0.0908)	−0.0250 (0.0301)	−0.0270 (0.0683)	−0.0017 (0.0051)	−0.0089 (0.0106)
Δ TAN_{t-1}	0.1365 *** (0.0460)	0.0630 *** (0.0091)	0.0007 (0.0013)	0.0310 *** (0.0054)	0.1345 *** (0.0407)	0.0217 * (0.0144)	0.0032 (0.0048)	0.0142 * (0.0108)	0.0005 (0.0008)	0.0043 *** (0.0017)
Δ NLR_{t-1}	0.0282 (0.0795)	−0.0303 ** (0.0157)	0.0038 * (0.0023)	−0.0082 (0.0093)	−0.0663 (0.0704)	−0.0429 ** (0.0248)	0.0091 (0.0082)	0.0799 *** (0.0187)	0.0023 ** (0.0014)	−0.0000 (0.0029)
Δ NG_{t-1}	0.2161 (0.1960)	0.0230 (0.0387)	−0.0005 (0.0057)	−0.0045 (0.0229)	0.1497 (0.1735)	0.0308 (0.0612)	−0.1247 *** (0.0203)	−0.0781 ** (0.0460)	0.0103 *** (0.0034)	−0.0184 *** (0.0071)
Δ Sil_{t-1}	−0.0564 (0.0926)	0.0190 (0.0183)	0.0040 * (0.0027)	0.0140 * (0.0108)	0.1232 * (0.0819)	0.0442 * (0.0289)	−0.0003 (0.0096)	−0.1011 *** (0.0217)	0.0021 * (0.0016)	−0.0004 (0.0034)
Δ Alu_{t-1}	1.3797 (1.2629)	−0.4089 * (0.2491)	−0.0008 (0.0370)	−0.2371 * (0.1477)	−1.7043 * (1.1182)	−0.0977 (0.3943)	−0.0489 (0.1308)	−0.1764 (0.2963)	0.0112 (0.0221)	−0.0080 (0.0459)
Δ HO_{t-1}	0.6249 (0.6262)	−0.1225 (0.1235)	−0.0160 (0.0184)	−0.0338 (0.0733)	−0.1760 (0.5545)	0.0026 (0.1955)	0.1525 *** (0.0649)	0.0267 (0.1469)	0.0127 (0.0109)	0.1972 *** (0.0227)
SP500	0.0080 (0.0495)	−0.0344 *** (0.0098)	−0.0018 (0.0015)	−0.0341 *** (0.0058)	−0.1361 *** (0.0438)	−0.0778 *** (0.0155)	−0.0130 *** (0.0051)	−0.0121 (0.0116)	−0.0001 (0.0009)	−0.0010 (0.0018)
STOXX50	−1.8849 (2.4829)	0.3256 (0.4898)	0.0915 (0.0728)	0.1091 (0.2905)	2.4580 (2.1984)	−0.3085 (0.7752)	0.2583 (0.2572)	0.3269 (0.5825)	0.0463 (0.0434)	0.0069 (0.0902)
Covid	−0.4182 ** (0.2144)	0.0396 (0.0502)	−0.0043 (0.0075)	0.0291 (0.0298)	0.1768 (0.2252)	0.0563 (0.0794)	0.0219 (0.0263)	−0.0623 (0.0597)	−0.0087 ** (0.0044)	−0.0039 (0.0092)
UKR	0.0783 (0.2058)	0.0431 (0.0406)	0.0020 (0.0060)	0.0670 *** (0.0241)	0.2770 * (0.1822)	0.2401 *** (0.0642)	0.0502 *** (0.0213)	−0.0183 (0.0483)	−0.0104 *** (0.0036)	0.0490 *** (0.0075)
Time	0.0002 (0.0002)	0.0002 *** (0.0000)	0.0001 * (0.0000)	0.0002 *** (0.0000)	0.0008 *** (0.0002)	0.0004 *** (0.0001)	0.0001 * (0.0000)	0.0001 *** (0.0000)	0.0001 (0.0001)	0.0001 *** (0.0000)
EC1	0.0021 * (0.0014)	0.0016 * (0.0011)	0.0002 * (0.0002)	0.0016 *** (0.0006)	0.0029 (0.0049)	0.0038 ** (0.0017)	0.0008 * (0.0006)	0.0035 *** (0.0013)	−0.0000 (0.0001)	0.0016 *** (0.0002)
EC2	0.0535 * (0.0371)	0.0208 *** (0.0073)	0.0011 (0.0011)	0.0253 *** (0.0043)	0.1289 *** (0.0328)	0.0618 *** (0.0116)	0.0115 *** (0.0038)	−0.0118 * (0.0087)	−0.0009 * (0.0006)	0.0044 *** (0.0013)
EC3	−0.0532 (0.0708)	0.0314 ** (0.0140)	−0.0012 (0.0021)	0.0285 *** (0.0083)	0.0098 (0.0627)	0.0474 ** (0.0221)	−0.0204 *** (0.0073)	0.0677 *** (0.0166)	0.0013 (0.0012)	−0.0043 ** (0.0026)

Note: Control Variables estimates are not reported for space reasons but are available upon request. Standard errors in parenthesis.

Table 1.7: Restricted VECM estimation.

nature of crude oil and solar energy. Figure 1.3 explains the difference between solar (complementary) and wind (substitute) energis.

(A) Capacity (B) Inst. Costs (C) LCOE



Source: IRENA (2022)

Figure 1.3: Renewable energies costs and capacity.

Given that the storage capacity of wind energy is considerably higher (and growing) than that of solar energy (panel A, Figure 1.3), the attractiveness of investments in wind power is greater than to those on solar. In other words, the reduced ability to actively maintain the stored energy of solar systems forces integration via fossil fuels (or renewable energies themselves).

The installation costs of solar power (panel B, Figure 1.3) have recently become lower than those of wind, leaving room for discussion on its future employment. However, as the International Renewable Energy Agency (IRENA) data show, wind energy has almost constant costs, which, being lower than those of solar energy until 2015, led interested economic actors to think of this energy as historically less expensive than solar energy. Furthermore, the Levelized Costs of Electricity (LCOE, panel C, Figure 1.3) confirm how wind energy leads to significantly lower expenses than solar energy. However, both energies seem to converge at the same level, thus signaling the recent efficiency gain of solar systems.

As a result, given the advanced stage of development of wind energy than solar energy, especially looking at its storage capacity, investors perceive this technology as a viable (current) alternative to fossil fuels. Furthermore, Kumar et al. (2015) show how the materials used to construct solar panels still require fossil fuels usage, increasing the complementarity between these two sources.[15] In this sense, it should

[15] A further indirect issue is that solar energy plants require a significant amount of land that is not always available. However, some alternatives are already being developed: agrophotovoltaics or floating photovoltaics.

be clear that the installed capacity of solar plants is almost zero compared with fossil fuels, indeed no replacement is taking place at the world level yet.

The estimated complementarity implies that solar energy systems cannot currently be considered an absolute substitute for fossil fuels (yet). On the other hand, it needs to be strengthened through subsidies and investments aimed at modern and sustainable facilities. Kalair et al. (2021) claimed the importance of nuclear fusion and artificial photosynthesis in expanding the storage capacity of solar energy. Carfora et al. (2018) argue that government intervention in this sector is relevant for its long-term development. Furthermore, together with the IRENA (2022) energy outlook, the expected high fossil fuel prices will consolidate the structural change that has seen renewable energy production become the least expensive source of new generation, allowing solar energy to become a viable alternative to fossil fuels. With the growing interest in renewable energy, investors and consumers can be sheltered from fossil fuel price shocks, avoid physical supply shortages, and improve energy security.

As expected, the increase in WTI and NG prices leads to decreases in heating oil quotations, indicating that global investors ar likely to see them as a substitute.

The impact of PBD on each of the considered renewable energy prices is consistently negative. However, the conclusions diverge looking at renewable energy as a whole. In this context, there is evidence of a complementary relationship between solar and wind energy, as indicated by the positive and statistically significant coefficients (confirming the result in Takle and Shaw, 1979; Song et al., 2022a). From an economic perspective, these findings suggest that wind and solar energy can be strategically combined in a policy mix to mitigate environmental degradation and foster the growth of renewable energy.

According to Ghandehariun et al. (2023) and Wang et al. (2023a), copper is one of the most used conduits in renewable energy systems. We expect that increases in copper prices may reduce the development of the renewable energy sectors. This result is confirmed for solar energy, while the effect on the wind and nuclear ETFs is marginal. The increase in aluminum price may reduce both TAN and FAN, signaling the influence of raw material prices in renewable energy development.

Since we run the non restricted trend case of the Johansen procedure, we estimate the time trend of each equation. The growth trend is significant for all renewable energy ETFs and commodity prices. Furthermore, it has great importance for fossil fuels, except crude oil. This result highlights the growing ESG (environmental, social, and governance) sentiment in the market as the performance of renewable energy companies increases.

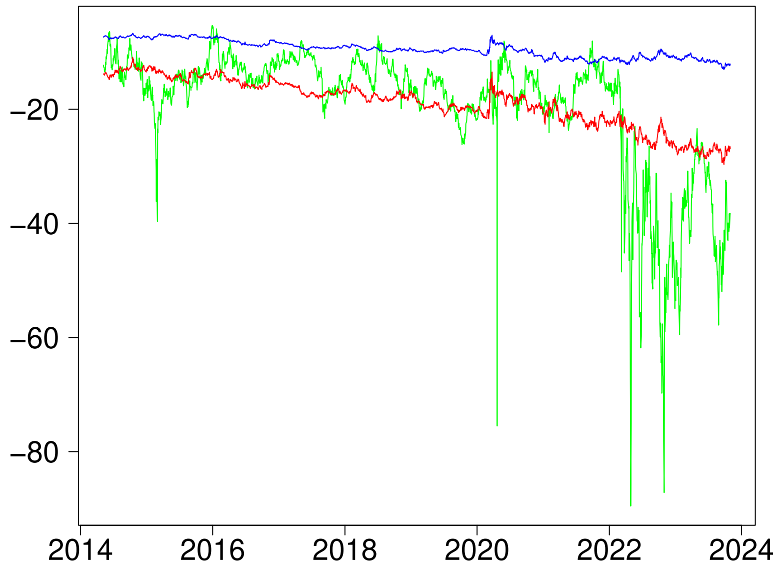
Error Correction Mechanism investigation

The restrictions applied to the cointegration matrix allow us to study the adjustment process toward long-run equilibria. The last three rows of Table 1.7 show the impact of the individual time series of the Error Correction Mechanism (ECM) on the endogenous variables. Since the ECM acts as a long-run corrector, the corresponding time series are negative (see Figure 1.4). Consequently, when considering the impact of the ECM on the single column of Table 1.7, if the estimated coefficient is positive, it is premultiplied by a negative ECM, thus resulting in a negative effect (contraction) on the series considered.

The first ECM (green in Figure 1.4) is significant for fossil fuels and silver, while the second (red in Figure 1.4) and third (blue in Figure 1.4) contribute more to renewable ETFs and commodity prices. Figure 1.1 reported the sudden increase in ETF prices in the middle part of the sample. The higher magnitude and statistical significance of the coefficients relating to the second error correction mechanism for renewables ETFs confirm that the second ECM refers to the correction mechanism of renewables.

Figure 1.4 shows the time series of the adjustment mechanisms. Since we are dealing with stock prices, these ECMs could be interpreted as market sentiment (partially following the discussion in Chiang and Tsai, 2023). An absolute increase in the magnitude of the ECM means that sentiment is also increasing. As a result, we need to understand how each ECM relates to different market sentiments.

The first ECM tracks the overall energy market sentiment since three focal points emerged: the relative decline in crude oil in the second half of 2014, the Covid-19 pandemic, and recent volatile behavior following the Ukraine crisis. The second and third ECMs show comparable behavior as they reached their positive peak after the Covid-19 pandemic. However, the second ECM shows a negative trend, which



Green line - ECM1, **Red line - ECM2**, **Blue line - ECM3**.

Figure 1.4: Error Correction Mechanisms (ECMs) Time Series

includes the need to adjust the growing trend of renewable energy ETFs. The values of ECMs are pronounced due to high stock price levels. Finally, the third ECM seems to correct the behavior of commodity prices. Given these observations, we build the following hypothesis scheme:

H1: the first ECM mainly refers to the general energy (fossil) market sentiment - Energy Sentiment;

H2: the second ECM accounts for a kind of ESG sentiment, referring to renewable energies development - ESG Sentiment;

H3: the third ECM seeks to correct the commodity markets prices - Commodity Sentiment.

To verify these hypotheses, we compare the ECMs behavior with the SP500 Energy Index, the iShares ESG Aware MSCI EM ETF (ESGE), and the WisdomTree Enhanced Commodity Strategy Fund (GCC), respectively as a proxy of (fossil) energy, ESG, and commodity sentiment.[16] Since ECMs are negative, we expect the behavior of the time series used as sentiment proxies to be theoretically reversed compared

[16]SP500 Energy: https://finance.yahoo.com/quote/%5EGSPE/, ESGE https://finance.yahoo.com/quote/ESGE/, and GCC https://finance.yahoo.com/quote/GCC/

to ECMs. In other words, we should observe a negative and significant correlation between the series to confirm our hypothesis.

Figure 1.5 reports the time series representation of the ECM, and market sentiment indices. To obtain a comparable measures, we report all the standardzed series. As expected, the behavior of ECMs seems to be reversed (on average) compared to the sentiments proxies. Moreover, the correlation values in Table 1.8 confirm our hypotheses. To ensure the robustness of our findings, Table 1.9 reports the nonparametric Pesaran and Timmermann (1992) test based on distances. Since the null hypothesis of the test is that the series move together we could conclude about ECMs as proxies for sentiment.

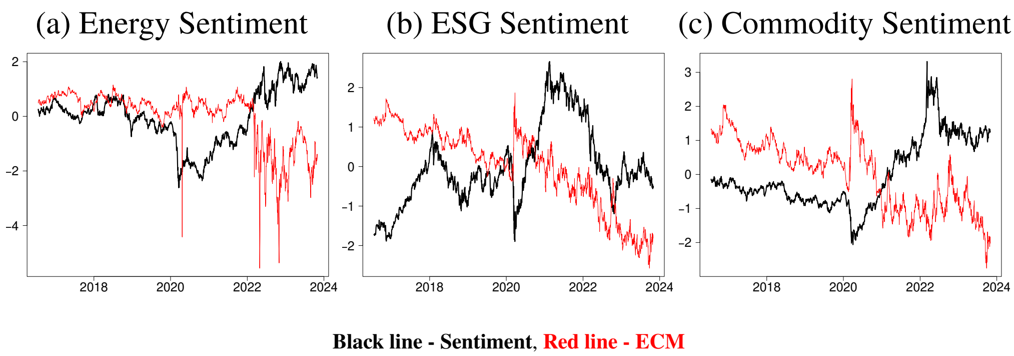


Figure 1.5: Standardized time-series

	Energy Sentiment	ESG Sentiment	Commodity Sentiment
ECM1	-0.56 ***	-	-
ECM2	-	-0.31 ***	-
ECM3	-	-	-0.71 ***

* : $5\% < p < 10\%$, ** : $1\% < p < 5\%$, *** : $p < 1\%$

Table 1.8: Correlation between sentiments and ECMs

The ECM and Sentiment series in Figure 1.5 diverged most between Covid-19 and the Russia-Ukraine conflict. This result is mainly due to two reasons. First, the ECM corrected the price increase of renewable energy ETFs. During this period,

Energy - ECM1	14.91***
ESG - ECM2	12.12***
Commodity - ECM3	35.6***

*** : $p < 1\%$

Table 1.9: Pesaran and Timmermann (1992) test.

companies have, on average, increased investments in the renewable energy sector, improving their ESG performance (Gamlath, 2020; Atkins et al., 2023). Secondly, the issue of climate change has led to an increase in adverse events, which have led to greater "social awareness".

Furthermore, we can confirm the results by analyzing the economic history of the last decade: until the Covid-19 pandemic, the energy market remained almost stable while ESG criteria started to increase, on average, after 2017. With the pandemic, the Energy sentiment declined while ESG sentiment peaked due to the desire to include more renewable energy components into the optimal energy mix. The outbreak of the war in Ukraine led the energy sentiment to decrease. However, in this case, the average market uncertainty leads to the common tendency for more frenetic behavior. These results are crucial from an economic perspective as overall energy market sentiment diverges from the ESG component.

From the analysis, we can also conclude that renewable energies will experience a growing trend. This conclusion is supported by the time series of the second ECM, which exhibits a negative trend with a higher absolute magnitude to correct the general ESG market sentiment. In addition, the current regulations and limitations for energy use are crucial to increasing the companies' usage of renewable energy sources. Our analysis is essential to explain the behavior of the renewable energy market in the context of the recent energy transition. On average, it seems that the ESG perception of investors is increasing,[17] further confirming the necessity of promoting industries and companies that use sustainable production ways.

1.4.2 Financial Spillover

In the context of growing instability, financial behavior is becoming massively studied by scholars and practitioners. In light of this, the results obtained from Section 1.4.1 are of fundamental relevance since it estimates the time series of each error term once we include additional financial information, such as prices, volumes, and market events. Therefore, the estimated error terms are ascribable to something that cannot be predicted by markets and investors when additional information is available.

[17] As stated among others by Eccles et al. (2017); Espahbodi et al. (2019); Park and Jang (2021).

Recently, the financial spillover literature strand has become popular across commodities. Several works analyzed the returns or estimated volatility spillovers (see, for instance, Foglia and Angelini, 2020; Liu and Hamori, 2020; Zhou et al., 2021, and others). In our case, we use the squared value of residuals (see, Andersen and Benzoni, 2008) as a proxy of realized variance and we standardize each time series in order to obtain comparable measures. In particular, the endogenous variables of Equation (1.10) are

$$x_t = \hat{\zeta}_t^{\,2} \tag{1.24}$$

where $\hat{\zeta}_t$ are the error terms from the cointegration model (see Equation 1.2). We include a graphical representation of innovations and the realized variance proxy in Appendix 1.A, Figure 1.13 and 1.14. As a result, the outcomes of our analysis can be relevant from a hedging perspective since it explains the volatility relationship between the series.

The volatility spillover is the transmission of instability from market/series "*i*" to market/series "*j*". It occurs when a sudden change in one market causes a lagged impact on volatility in another market above the local market effects. Some authors defined the spillovers as the "contagion effect" derived from changes in series volatilities.[18]

Static analysis

Figure 1.6 presents the static pairwise spillover index of realized volatility for renewable energy ETFs, raw materials, and fossil energies innovations with the additional consideration of the volatility of the American and European benchmark indices.[19]

We based our results on a VAR of order 1 (determined by the BIC information criteria) where the vector of endogenous variables x_t in Equation 1.10 is composed of all the proxied realized variances ($K = 12$). The Generalized Forecast Error Variance Decomposition (GFEVD) expressed in Equation 1.12, is based on 70-step-ahead forecast errors. According to the Diebold and Yilmaz (2012); Diebold and Yılmaz

[18]We follow the original definition of Forbes and Rigobon (2002) despite many definitions were introduced in the corresponding literature, (see, among others Sachs et al., 1996; Allen and Gale, 2000; Dornbusch et al., 2000; Pritsker, 2001).

[19]The volatilities of the American and European benchmark indices (SP500 and STOXX50) are computed using the squared daily first difference of logarithmic closing prices.

(2014) (DY) theoretical framework, the step-ahead number should be a limit beyond which the results obtained are comparable, *i.e.* exhibit similar behavior. Accordingly, after 70 periods, the spillover results stabilized.

In Figure 1.6 we report the $K \times K$ matrix of pairwise spillovers obtained from the DY application. While the main diagonal reflect the own-variable spillover caused by the self-caused variations within a given market (these are not particularly interesting in our context), the off-diagonal elements ($i \neq j$) measure the market cross-spillovers. Each entry in the heatmap is the estimated contribution of the innovation in market j to the GFEVD of market i (*i.e.* the pairwise relationship). For instance, the first column measures the directional connectedness from crude oil to other markets (i.e., $\mathbf{S}_{WTI \rightarrow j}$) and so on for the others, and vice-versa for the rows.

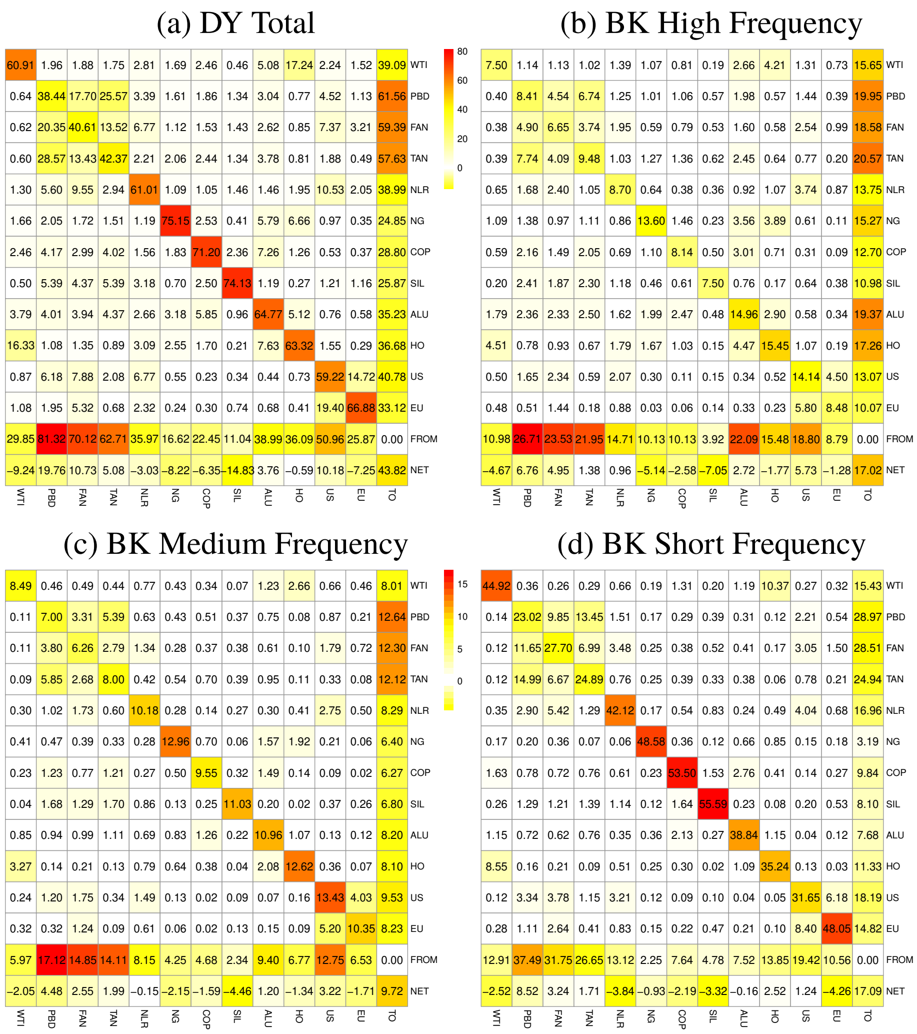


Figure 1.6: Static Spillovers: DY and BK

In Section 1.3.2, we derived four measures of contagion (TOTAL Eq 1.14, FROM

Eq 1.15, TO Eq 1.15, NET Eq 1.16). Figure 1.6(a) reports the DY pairwise net spillovers heatmap. The directional spillovers are listed in the last two rows (FROM and NET), the latter column (TO) and the last cell reports the Total Spillover Index (TSI), which amounts to 43.82, meaning that relevant evidence of interconnection between the variables emerged.[20]

According to Figure 1.6(a), some features emerged mainly for renewables innovations. The volatility of the solar market explains around the 25% variation in total renewables innovations (PBD), while the Eoilc makes up 18%. The spillovers from raw materials to renewables are around 5%.

The relationship between renewables and American and European market indices is not pronounced except for wind energy (near 10%), confirming Lundgren et al. (2018) and demonstrating investors' care about a novelty from more sustainable mechanisms.

As opposed to Umar et al. (2022) and Foglia and Angelini (2020), the Crude Oil turns out to be marginal in our model, confirming Ferrer et al. (2018). This result is due to the dummy imposition in Section 1.4.1 fixed to catch peaks in WTI prices. The only notable exception is the relationship with Heating Oil. Financially, this result is attributable to the difference between speculative and fundamental parts included in the Crude Oil market price. While the spillover impacts exclusively on the fundamental part, the role of the speculative one is essential in generating market turmoils.

Looking at the last row of Figure 1.6(a), renewable energies, except Nuclear, seem to emit volatility, while fossil fuels and raw materials act as volatility receivers. Among others, this result confirms Attarzadeh and Balcilar (2022); Le (2023), while it does not agree with Ahmad (2017), which found a relevant role as volatility emitters of fossil fuels.

This outcome has significant financial consequences for investors as movements in clean markets, particularly those of wind and solar industries, can result in significant market fluctuations, thus leading to hedging considerations. Several opportunities have emerged for investors to optimize their portfolios and manage risks. Investors

[20]Several papers typically compare spillovers from estimated volatilities from the GARCH model and returns (Maghyereh et al., 2016; Kang et al., 2017; Dahl et al., 2020). However, since this work is based on innovations from a cointegration model, we do not consider results with returns.

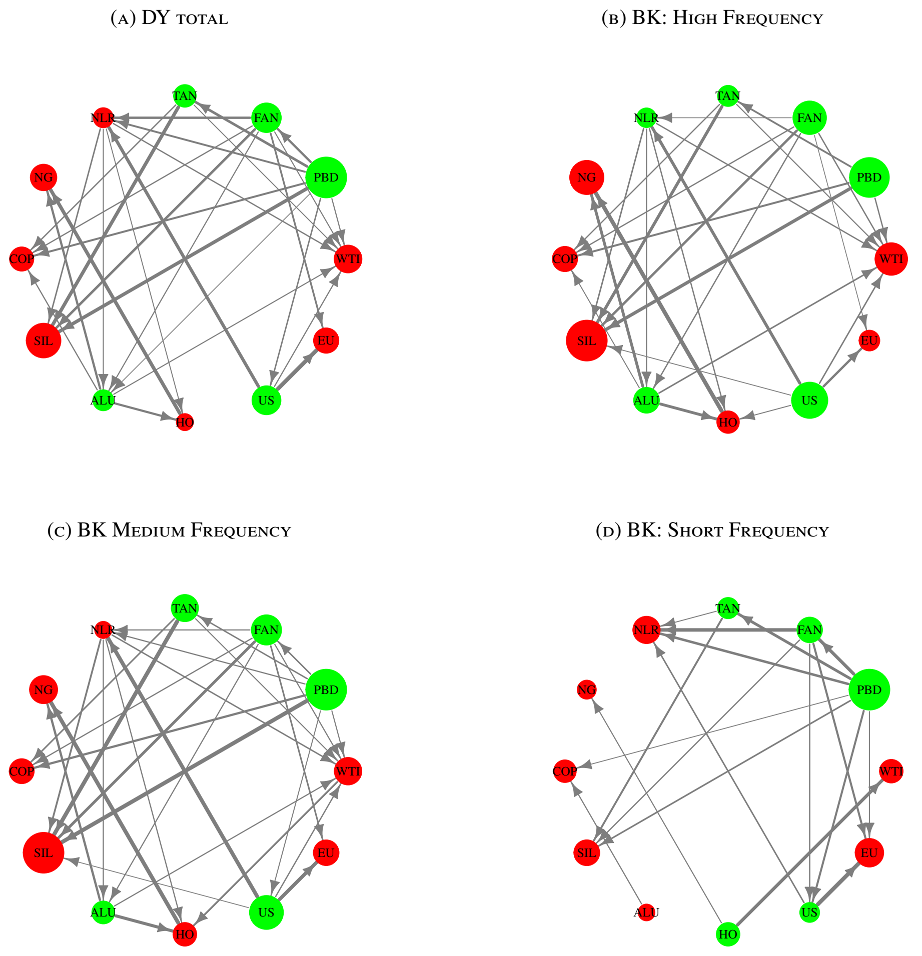
interested in renewable energy should consider hedging strategies to mitigate volatility, while those trading in fossil fuels and commodities should carefully evaluate their exposure and consider the speculative and fundamental aspects of the market.

To extend the literature contribution of this paper, we include the Baruník and Křehlík (2018) frequency spillover. We follow the related works in this field to identify three frequencies: high (1 to 5 days - short period), medium (5 to 10 days - medium period), and low (10 to 20 days - long period).

As reported from Figure 1.6(b)-(d), the highest Total Spillover Index (TSI) is associated with the highest (17.02) and lower (17.09) frequency, followed by medium (9.72) term. The average volatility spillover from any market transmitted to other markets has immediate effects, improving the result in Ferrer et al. (2018), who did not consider the Covid-19 pandemic and Russia-Ukraine war. Baruník and Křehlík (2018) explained that periods in which high-frequency spillovers are generated seem to lead financial markets to process information quickly. Our finding aligns with Liu and Hamori (2020) and Zhang and Hamori (2021), who also found a long-term persistency in volatility spillovers. They claimed the importance of structural market breaks in influencing the perception of financial series, as we will see in the dynamic analysis. Since the information is quickly processed in the energy and commodity markets, the implications for hedgers are relevant since they need to constantly control their portfolio optimizations.

The relationships across the network are shown in Figure 1.7. In this case, the color node represents the role of the series (red - receivers, green - emitters) and the size of the cumulated spillovers emitted/received. Edges are reported if the volatility contribution is higher than 20% on the GFEVD. From this analysis, the role of the PBD is emphasized in almost every series, for every frequency. Solar and wind energy influence the commodity sectors. The US market leads the EU index, signaling the influence of American sentiment on European sentiment, which generally lags.

To ensure the robustness of our results, in Appendix 1.C - Figure 1.17 and 1.18 - we report the same connection measures calculated on squared log-differences, used as volatility benchmarks. Although the spillover coefficients are different, the conclusions are the same. The spillovers occur in the short term, with the relevant role of renewable energy financial products in influencing other markets. In addition, WTI



Note: When the node with the name of the series is red (green) it means that the series receives (emits) volatility. The thicker edge means the higher contagion between innovations.

Figure 1.7: Network net volatility spillover

is a volatility receiver, highlighting how dependent the fossil market is on external market conditions, thus confirming the uncertainty in the fossil energy market.

Covid-19 splitting

In the context of financial markets, the impact of Covid-19 has garnered substantial attention in academic research. Numerous studies have explored how this event influenced market performance.[21] We partition our dataset into two segments, before (length of the sample 1457 observations) and after (length of the sample 990

[21] He et al. (2020); Baek et al. (2020); Uddin et al. (2021); Zaremba et al. (2021).

observations) December 31, 2019.[22] Due to space constraints, we have included all the estimations in Appendix 1.B for reference. Notably, the DY spillover exhibits the highest TSI after the outbreak of the Covid-19 pandemic, amounting to approximately 34.46%, compared to the pre-pandemic 25.76%. This finding suggests that the pandemic led to an elevated level of interconnectedness among financial markets, with a particular shift of attention towards renewable systems. Furthermore, the spillover effect from WTI becomes more pronounced in the post-Covid-19 sub-sample. It transforms into a net volatility emitter, demonstrating intriguing relationships with raw materials.

Many differences emerge between Figures 1.15 and 1.16 (in the Appendix), especially according to the connectedness spread between Renewables and Materials. The variation in the influence of indices and the progressive change towards a reduction in dependence on WTI innovations led the post-COVID spillover to develop more in renewable energy markets. The increase in significant renewable spillover confirms investors' interest in more environmentally sustainable investments. Therefore, the innovations in these markets produced appealing connections with the materials used. We saw in Section 1.4.1 the significance of the price of copper for the renewable cointegrating vector, confirming the energy dependence on that material. The BK findings are consistent with the ones obtained from the whole sample.

Therefore, by merging the cointegration analysis with this one of financial spillovers, it is possible to notice how, after the Covid-19 disease, the volatility for the entire innovations increased with some change in variable relevance, being in line with Geng et al. (2021). Indeed, aluminum has become a relevant source of volatility, reinforcing the findings from the cointegration: in the short-run, a negative statistically significant relationship between aluminum and renewables emerged. Furthermore, the interconnection between materials innovations was enhanced, emphasizing the role of aluminum as a net-volatility emitter. As well as the full-sample analysis, the Baruník and Křehlík (2018) split spillover frequencies confirm the short-period TSI higher than the others in both sub-samples. This splitting is the base for the dynamic analysis. It aims first to discover the time-connectedness of the variables and second

[22]The lengths are 1475 and 1000 respectively for pre and post December 31, 2019.

to overcome the issue of the static Diebold and Yilmaz (2012) methodology, which fails to identify the significance of results.

Rolling dynamic analysis

The static analysis provides a general idea of the volatility connections over the entire period. However, it does not help us understand how connectedness changes over time. Since we have recently gone through a worldwide pandemic, and wars are ongoing,[23] a dynamic rolling window analysis could improve the robustness of this work. Including the time component is crucial to underline some aspects that the general static measures fail to individuate.

In detail, based on the full length of the timeseries (from May 8th, 2014) we estimate the VAR model in equation (1.10) using a 250-day rolling window as in Toyoshima and Hamori (2018), which roughly refers to a year of trading days.[24] In this way, according to Lovcha and Perez-Laborda (2020), we could determine the time-varying TSI defined in Equation (1.14) to understand the periods of higher and lower interconnection.

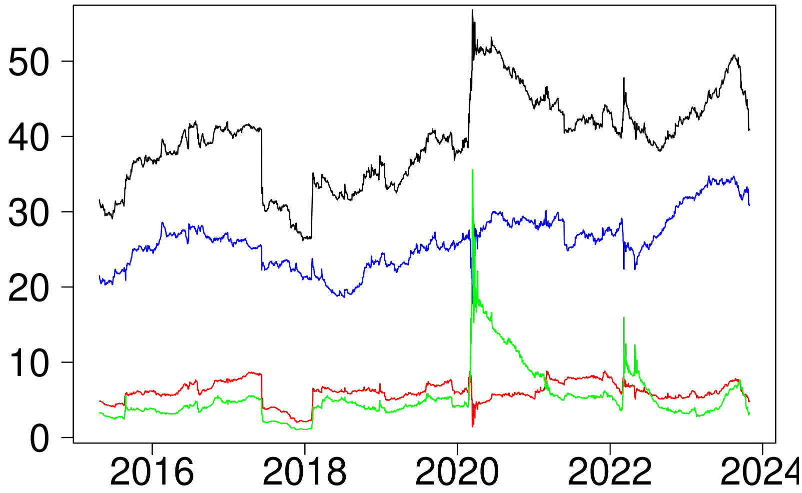
First, we report in Figure 1.8 the dynamic aggregate TSI. Looking at the dynamic TSI in Figure 1.8, most volatility spillovers occurred in the short period. The only notable exception was the Covid-19 pandemic, where the long-run TSI peaked, highlighting the role of Covid-19 in the structural behavior of the financial market. This result is significant because it highlights how, at the beginning of the pandemic, the expectations of economic and financial actors were significantly negative, especially given the non-existence of vaccines and a potential treatment for Covid-19.

In contrast, the behavior of the volatility connection in the medium run is more homogeneous, indicating constant and stable spillover around 5-10 days.

According to the results obtained in the cointegration analysis, the Russia-Ukraine war had a more pronounced impact on stock prices. Conversely, the Covid-19 pandemic was associated with higher volatility spillovers between the different series, confirming Li et al. (2022a). From a financial markets point of view, this evidence

[23] In addition to the war in Ukraine, the conflict in Gaza has also influenced financial markets.

[24] As we did for the step-ahead number (static analysis), we conducted several trials using different rolling schemes higher than 250, with almost comparable results.



Black line - DY Total, **Blue line - BK high**, **Red line - BK med**, **Green line - BK low**

Note: The Total Spillover Index is computed via Equation (1.14). It is a volatility connectedness measure that ranges from 0 to 100.

Figure 1.8: Dynamic Total Spillover Index.

suggests that the pandemic effects had broader and more unpredictable effects on financial markets, causing turbulence across various sectors beyond just energy and raw materials. In addition, this implies that geopolitical events referring to global energy suppliers (such as Russia) can directly affect the market prices of different sectors, especially those from energy and raw materials. This pattern is confirmed in Figure 1.19, where we report the rolling TSI on standard squared returns.

The dynamics of net volatility spillovers are illustrated in Figure 1.9 and 1.10.

On average, Aluminum and Silver receive volatility spillover in almost all the timespan considered. However, copper started to emit volatility spillovers after the Russia-Ukraine conflict and consequent material crisis, as previously stated by Mensi et al. (2022). This observation aligns with the findings of the cointegration analysis, highlighting the copper price relevance in the context of renewable energy pricing.

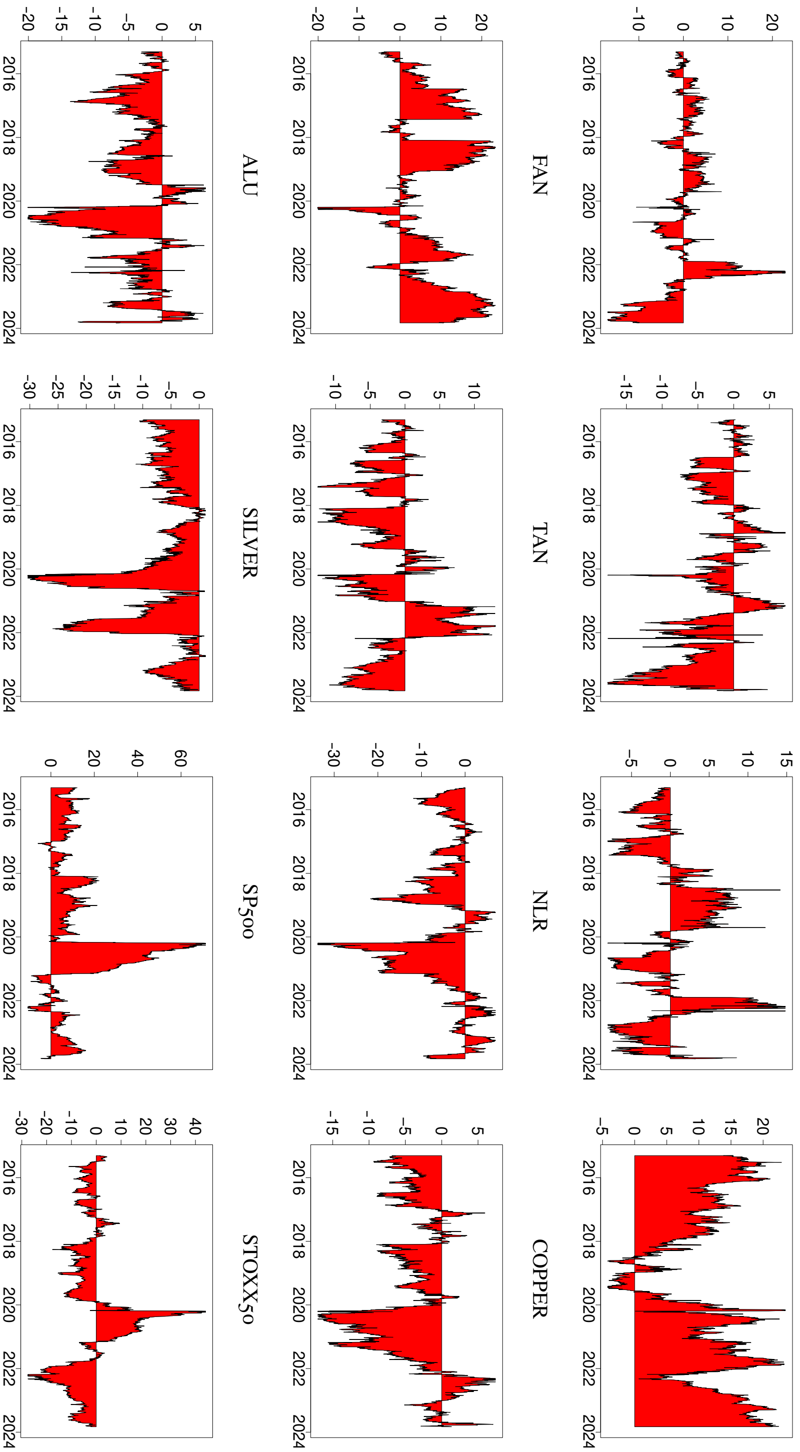
Except for Nuclear energy, which receives volatility spillovers in almost all the samples, the behavior of solar and wind sectors is non-homogeneous, corroborating Hanif et al. (2023). Aside from the general renewable ETF (PBD), both the solar

(TAN) and wind (FAN) sectors display positive and negative peaks. This result partially agrees with Shahzad et al. (2022), who describe wind energy as the largest transmitter of shocks in financial markets, while it received volatility spillovers during the Covid-19 period.

Notably, the observed volatility coincides with the peaks registered by fossil fuels, especially during the Covid-19 and Russia invasion (Dutta and Dutta, 2022). Economically, rising fossil energy prices stimulate heightened investor interest in renewables, thereby enhancing their significance. Consequently, this complex relationship leads to increased volatility, which in turn influences the other considered series (aligning with Zhou et al., 2021). All these features are confirmed by the robustness analysis conducted in Figure 1.20, where the squared returns are used as volatility benchmarks.

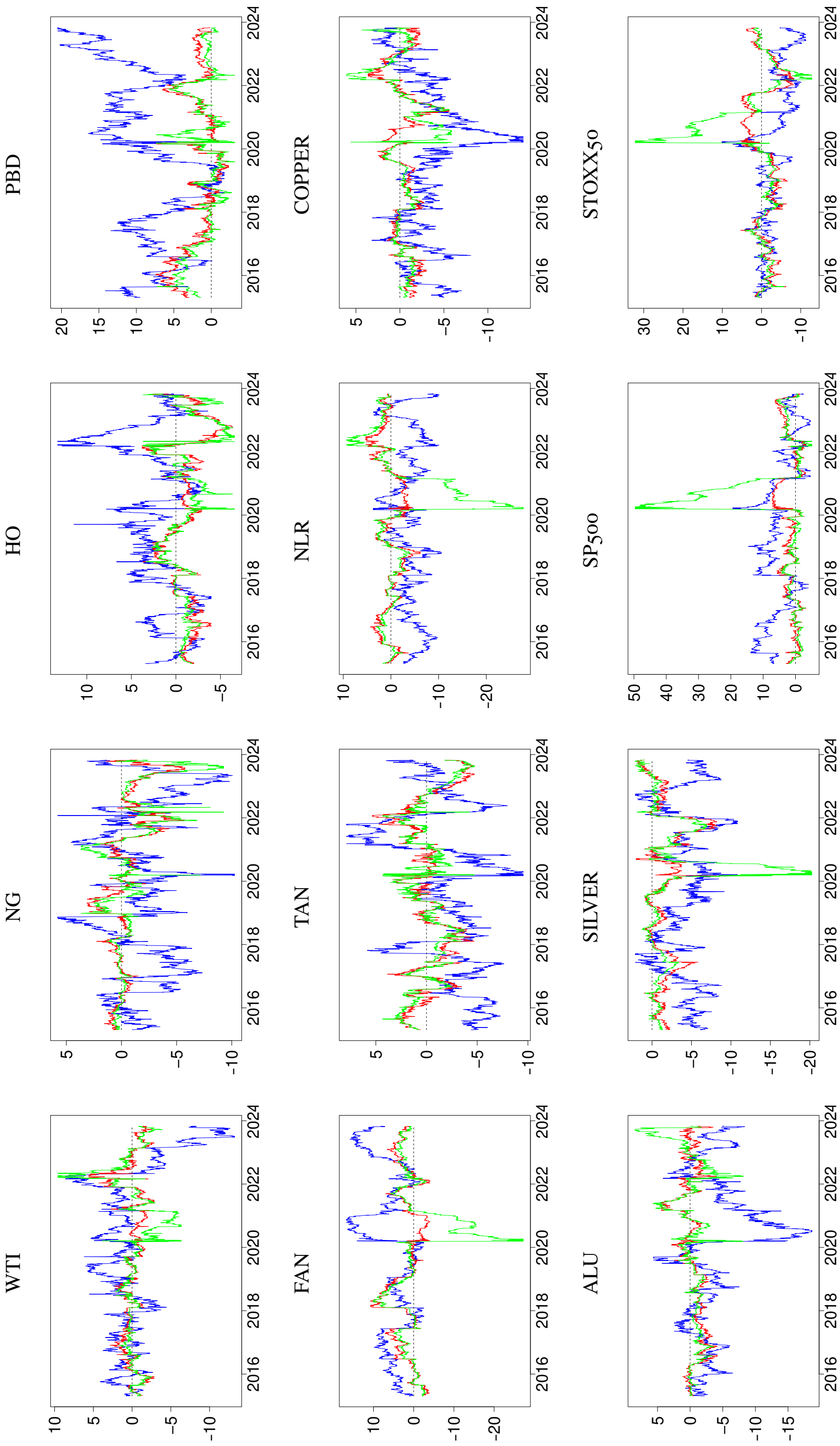
Despite the fall in Oil Prices during the Covid-19 period and the turmoils generated in the energy market by the Russia-Ukraine conflict, the behavior of Crude oil within this volatility spillover system appears to be mixed before the pandemic but after, during the highest turmoils period, it receives spillovers from other markets. The behavior of Natural Gas and Heating Oil is similar to those of the WTI, reversing the findings of Yadav et al. (2023), which found Natural gas to be the highest contributor of the shocks while confirming crude oil as the net volatility receiver from the network connection.

On the other hand, considering different spillover frequencies enlarges the research. In Figure 1.10, we report the Baruník and Křehlík (2018) spillovers where the blue line shows the high-frequency spillovers (1-5 days), the red line refers to the medium frequency (5-10 days), while the green line represents the long period (10-20 days). Renewable energies (except nuclear) have produced relevant high-frequency volatility spillovers. In particular, wind and solar energy systems generate immediate volatility spillovers to the system. From an economic perspective, this result is slightly profitable because it shows how renewable energy innovations have a significant prompt consequence on financial systems. Nonetheless, under specific conditions, the wind market produces low-frequency spillovers. In particular, in the early part of the sample, it receives turbulence from other markets at low to medium frequencies.



Note: If the spillover is positive the series emits spillover, while if the spillover is negative, the series receives spillovers.

Figure 1.9: Diebold & Yilmaz Net Spillovers



Black line - DY Total, **Blue line - BK high**, **Red line - BK med**, **Green line - BK low**

Figure 1.10: Barunik & Krehlik Net Spillovers

Moreover, in early 2018, the development of the renewable industry caused significant long-run spillovers in all financial systems, except for wind sources. This result, combined with the high dependence on higher frequencies, indicates that renewables energy sentiment is becoming prominent in portfolio choices and optimal asset allocations since it influences the investors' risk management. However, during the Covid-19 pandemic, these series receive spillovers, also in the long term, signaling a volatility dependence during this event.

Regarding fossil fuels, we notice some interesting patterns in how frequency volatility spillover spreads. WTI (West Texas Intermediate) plays a prominent role in transmitting volatility, especially over longer time frames until the Russia-Ukraine war. However, it tends to receive volatility spillovers in the short term. There is a notable exception during the energy crisis caused by the Russia-Ukraine conflict, where WTI, Natural Gas (NG), and Heating Oil (HO) all started emitting volatility. Heating Oil behaves similarly to WTI, while Natural Gas consistently acts as a receiver of volatility across various time frequencies, confirming Umar et al. (2022) and Mensi et al. (2022).

Commodity prices typically receive volatility. However, their behavior diverged during the Covid-19 epidemic. Notably, aluminum received low-frequency spillovers, indicating a more structural interdependence within the network. In contrast, copper and silver experienced substantial short-term spillovers after the Covid-19 pandemic, thus confirming (Adeleke and Awodumi, 2022).

The US market emits volatility spillover for almost all the period considered, with a long-term peak around the Covid-19 pandemic. The behavior of the European system is, on average, different from the American system since it receives volatility spillover. It still exhibits several peaks, but the American markets exceed Europe in the highest frequency. This difference between the European and American systems raises the question of how investors view renewable energy: an immediate market reaction signals a consistent change in investor sentiment toward renewable energy. Quite the opposite, a slow response may underscore the market's willingness to wait and see what happens. In practice, it is synonymous with the investors' social caring about investments.[25]

[25] The BK spillovers are confirmed by the robustness analysis conducted in Figure 1.21.

Pairwise Spillover Analysis

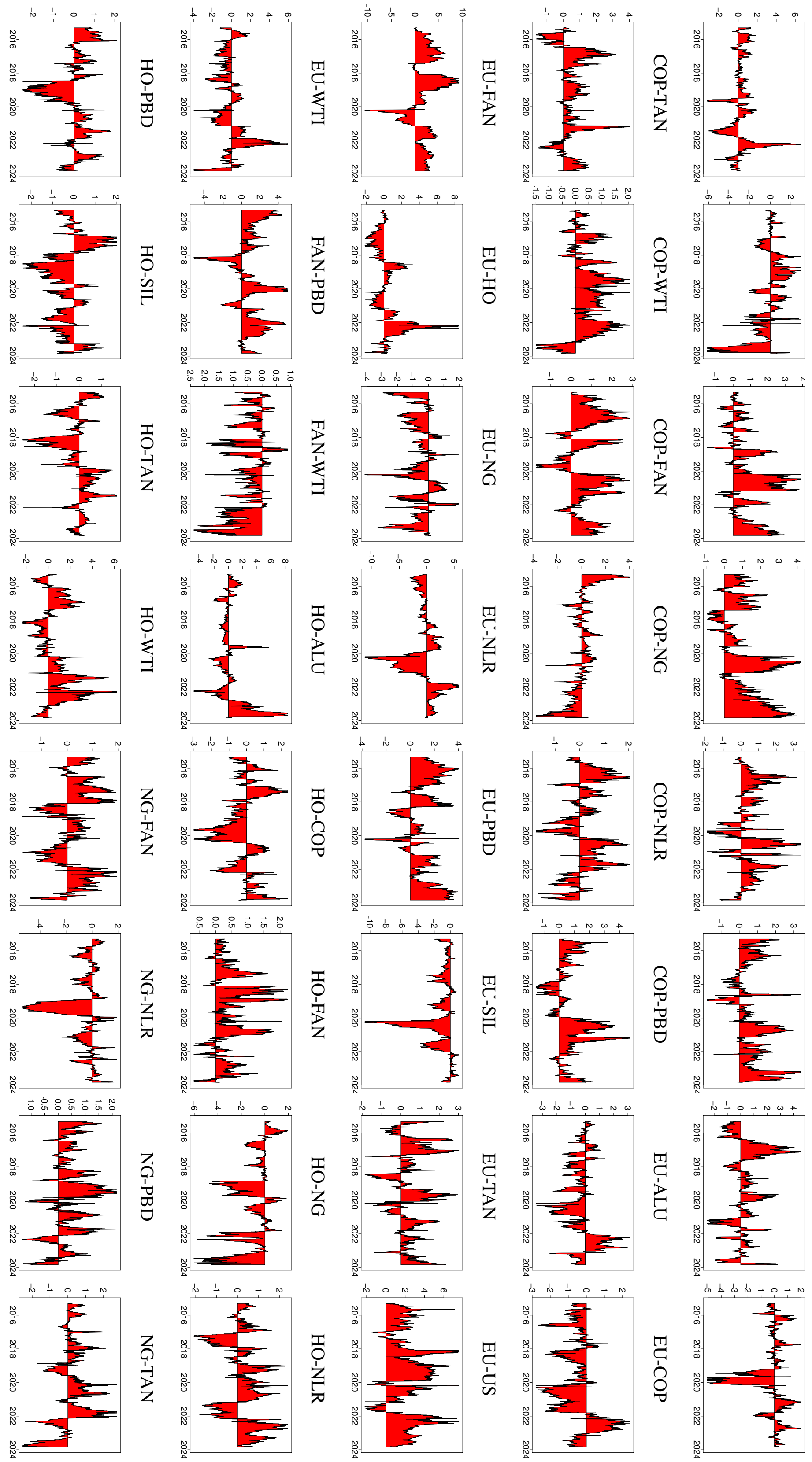
Figure 1.11 and 1.12 report the pairwise spillover analysis. The role of the US market as an emitter of volatility is exacerbated with the onset of the Covid-19 pandemic. Although it emits volatility repercussions during almost the entire time frame, it shows significant peaks during the initial market collapse due to the spread of Covid-19 and the measures to contain the contagion. All the renewable energy ETFs began to influence European market volatility after the second half of 2021, when the economic recovery began, thus confirming the increasing investors' social awareness.

While WTI receives volatility spillovers from renewable energy even during the recent conflict between Russia and Ukraine, natural gas and heating oil increase volatility in every renewable sector except FAN, thus making wind industries a profitable hedging opportunity. The volatile behavior of aluminum and silver was confirmed during the Russia-Ukraine conflict. However, the commodity crisis caused by the war caused copper to emit significant volatility spillovers on solar and nuclear systems while receiving spillovers from FAN and PBD. In this sense, we confirm Valckx et al. (2021), concluding how copper prices and volatility are crucial for renewable energy investments.

Recently, wind and solar energy emit volatility spillovers to silver and aluminum, while they receive volatility spillovers from copper. Nuclear energy appears to behave as a volatility receiver, with the only noteworthy spike occurring at the start of the Russia-Ukraine war, when fear of nuclear war began to spread across economies. This result highlights how this type of energy is usually considered marginal in stable market situations, compared to wind and solar, which are used more because they are considered safer and more profitable (Kath et al., 2020). We do not report results from the Baruník and Křehlík (2018) perspective to facilitate discussion, but the consequences of volatility fade within a week in almost all pairs.[26]

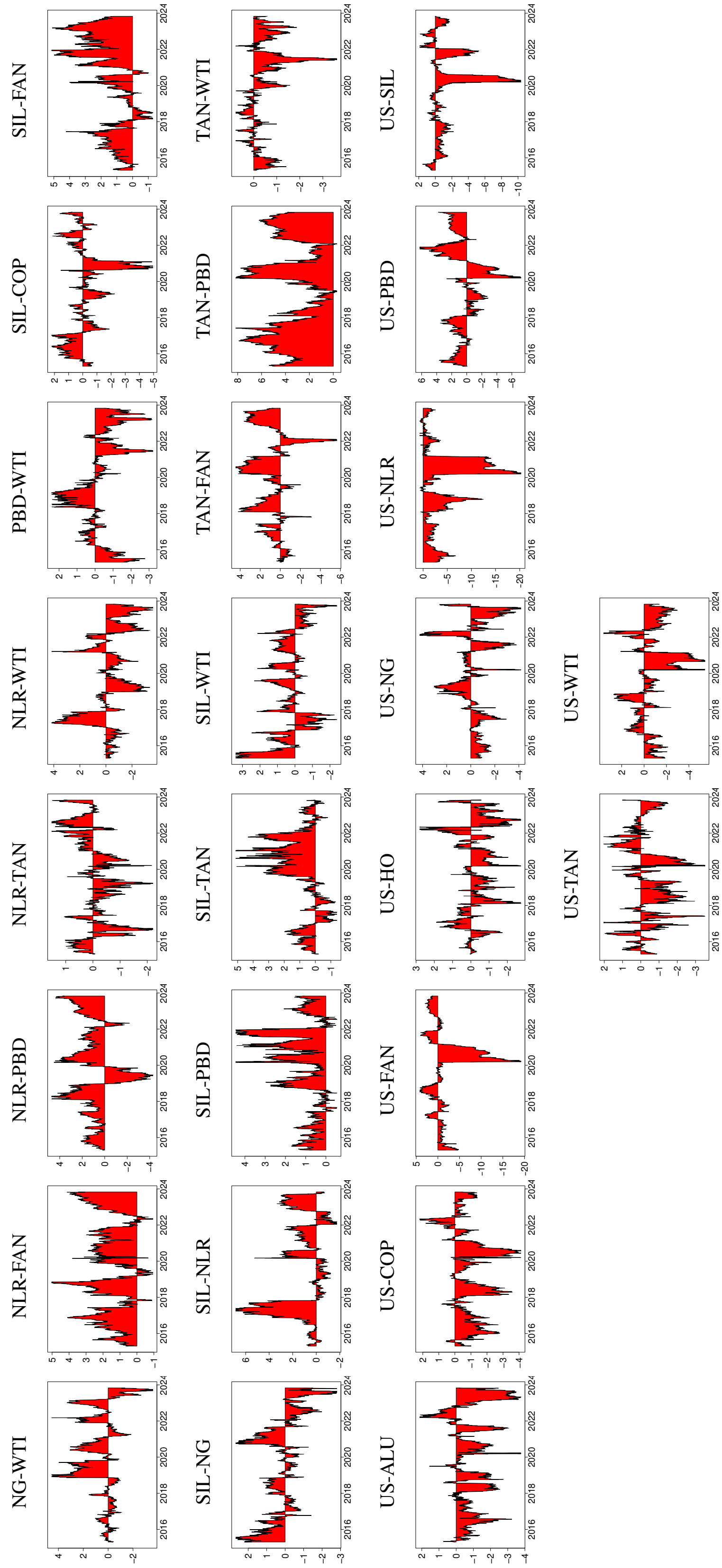
These results leave room for some recommendations. Investors should monitor the evolving dynamics of volatility spillovers in energy markets, particularly during turmoil events like the Covid-19 pandemic and geopolitical conflicts. These events can present both investment opportunities and risks, and understanding the impact of

[26]For reasons of space, we do not report the robustness version of Figure 1.11, but the results are also confirmed in light of previous robustness checks.



Note: If the spillover is positive the first series receives spillover, while if the spillover is negative, the first series emits spillovers.

Figure 1.11: Diebold & Yilmaz Net Pairwise Spillovers (part I)



Note: If the spillover is positive the first series receives spillover, while if the spillover is negative, the first series emits spillovers.

Figure 1.12: Diebold & Yilmaz Net Pairwise Spillovers (part II)

specific commodities, such as copper, on the renewable energy sector is crucial. Market preferences for energy sources (especially for wind and solar sources considered safer and more profitable) can lead to portfolio rebalancing and short and long-term investment choices, especially when considering raw materials such as copper. It is worth noting that these volatility spillovers tend to have short-term effects, typically lasting no more than one week, which underscores the need for timely decision-making in response to changing market conditions.

1.5 Conclusions

With the increasing global environmental pollution and energy crisis, investment in renewable energy has become a concern for investors in recent years. In this study, we first deepen the study of the cointegration relationship held for the energy variables and the raw material prices. To generalize the work, we used ETFs to identify solar (TAN), wind (FAN), and nuclear (NLR) markets to produce sectorial reports. Then, residuals from VECM models are squared and considered as volatilities proxies. As a result, we conduct a volatility spillover analysis using the Diebold and Yilmaz (2012) and Baruník and Křehlík (2018) methodologies.

We identified a cointegrating relationship among the variables, confirming a long-term relationship among various energy sources, including fossil fuels and renewables, along with raw material prices. The relationship between wind and crude oil aligns with the findings in Bondia et al. (2016), which suggested a substitution relationship between fossil and clean energy sources. Quite the opposite, we confirm a kind of complementarity relationship between solar energy and fossil fuels, confirming Dominioni et al. (2019).

While the Ukrainian war influenced almost all the series, the Covid-19 dummy does not impact prices, except crude oil. Interestingly, the American financial swaps, meant as volumes rise, led renewable energy performance to decrease during turmoil (higher volatility) periods.

The static volatility spillover connectedness analysis revealed the influence of renewables on raw materials. Moreover, a bidirectional relationship between returns and clean innovation emerged. We reported the unexpected result of WTI that, on average, does not transmit volatility spillovers. Furthermore, decomposing the spillover frequencies showed a certain persistence of volatility transmission mechanisms, settling at around five days.

Conversely, from a dynamic rolling perspective, the WTI is a net emitter of volatility during turbulent periods for almost all the employed series and with some long-lasting effects. During market turbulence, the interconnectedness between the series increased, showing a willingness to substitute fossil energy with renewable ones in portfolio optimization. Moreover, the raw materials sector became a net volatility innovation receiver encompassing the role of "system stabilizer", thus not contributing to increases in global market uncertainty.

1.A Innovations and realized volatilities

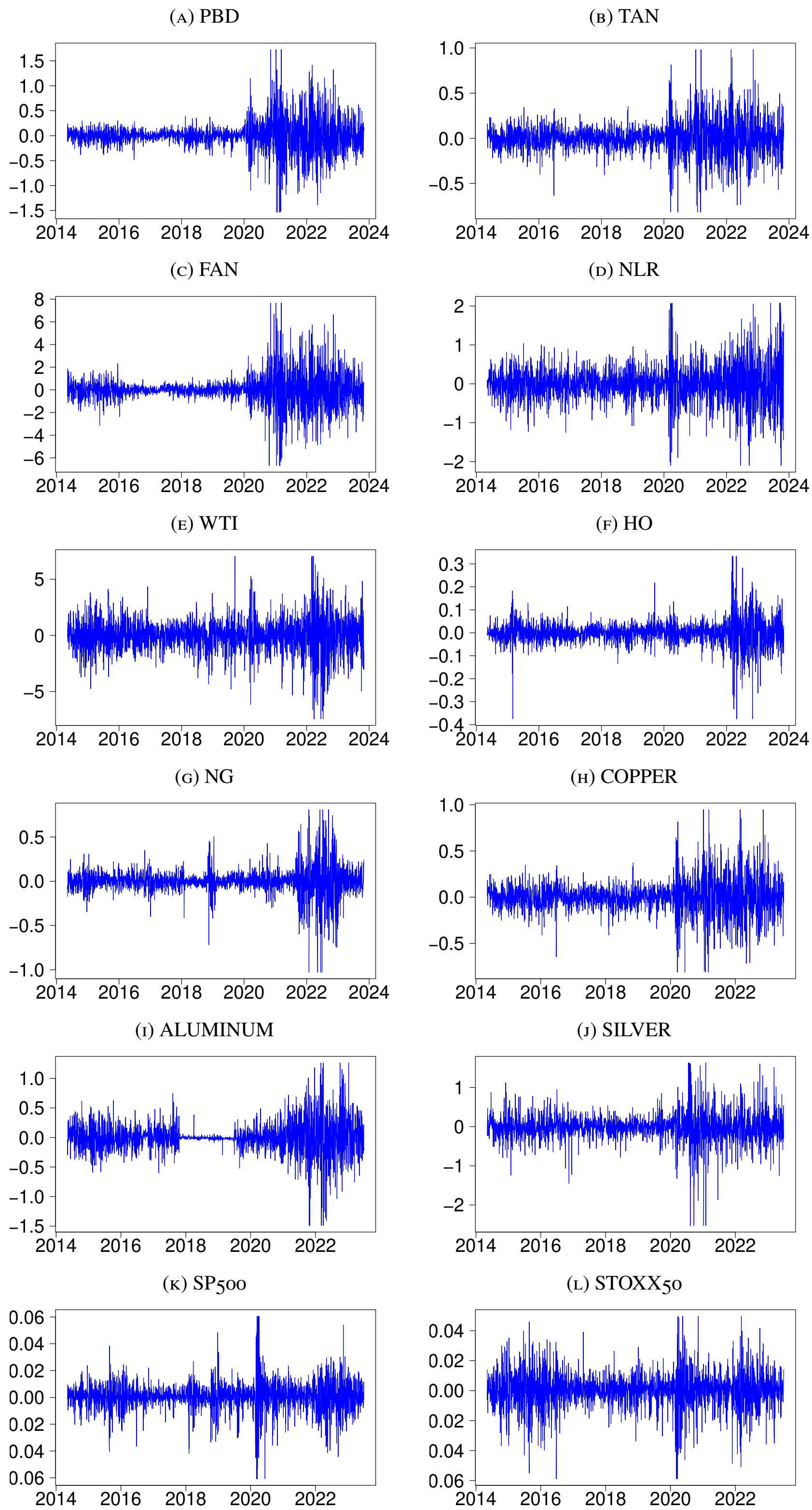


Figure 1.13: Innovations from cointegration analysis.

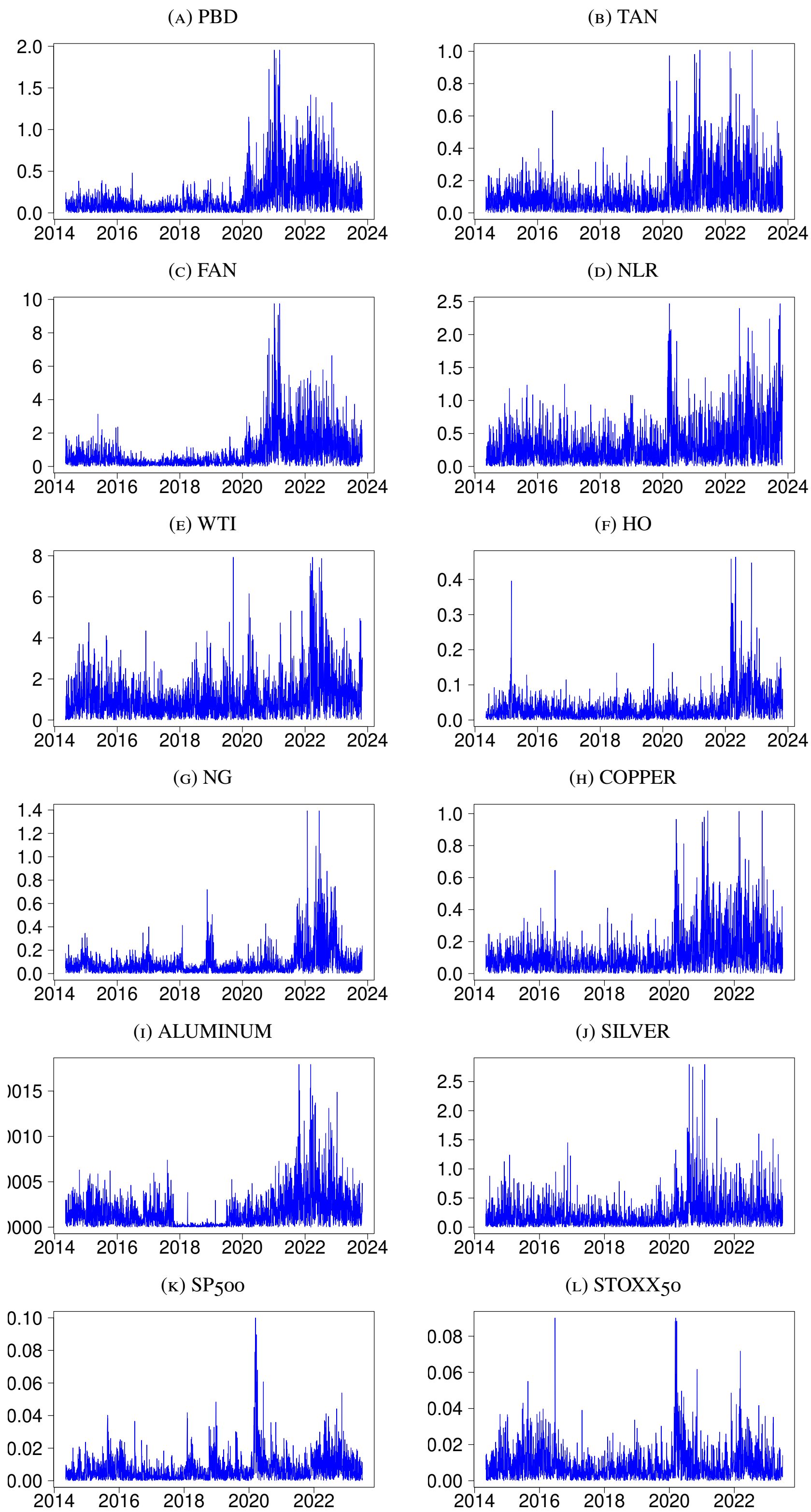


Figure 1.14: "Realized" Volatilities.

1.B Covid estimation splitting

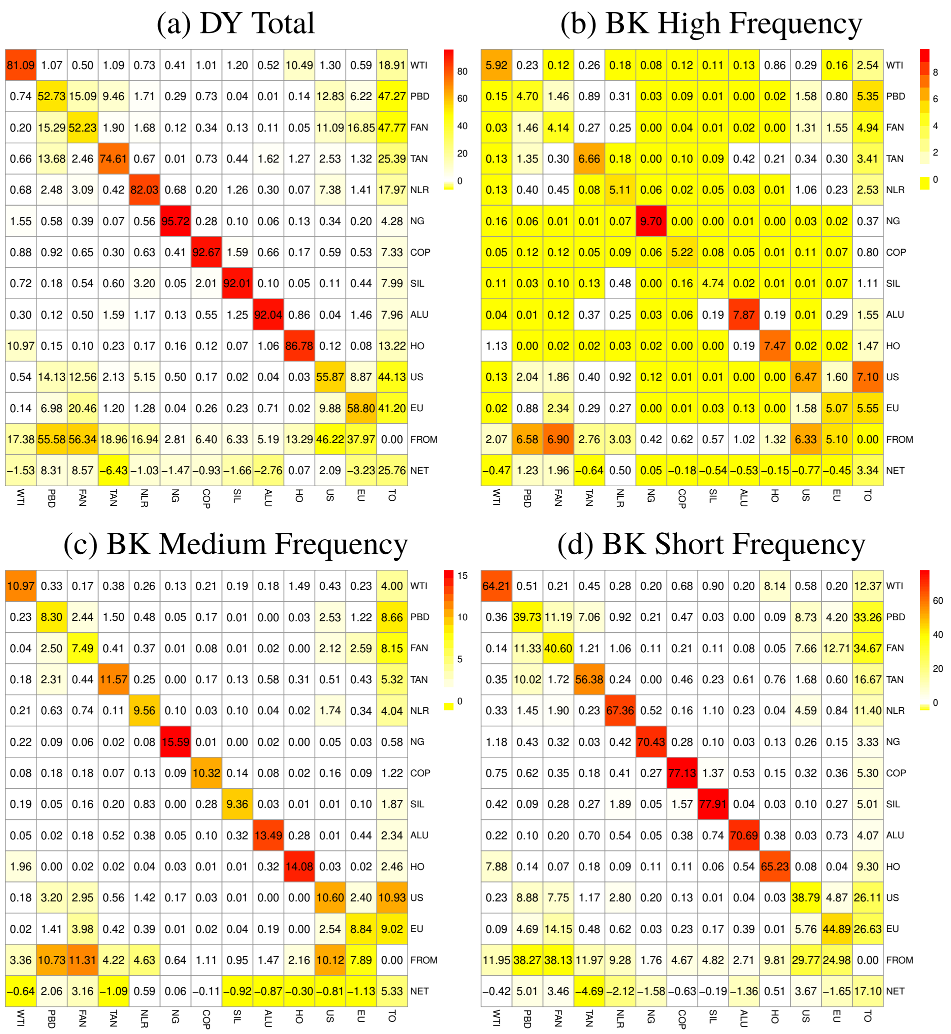


Figure 1.15: Pre Covid Spillovers both DY and BK

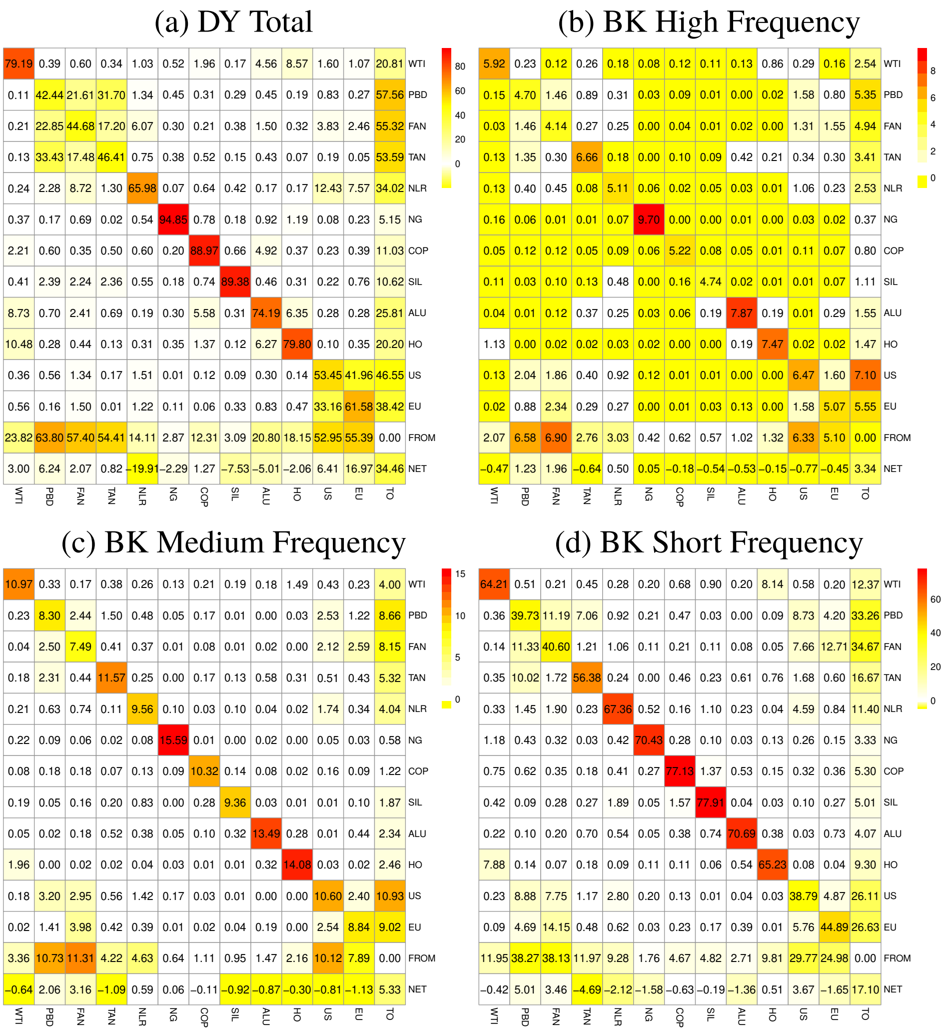


Figure 1.16: Post Covid Spillovers both DY and BK

1.C Robustness check

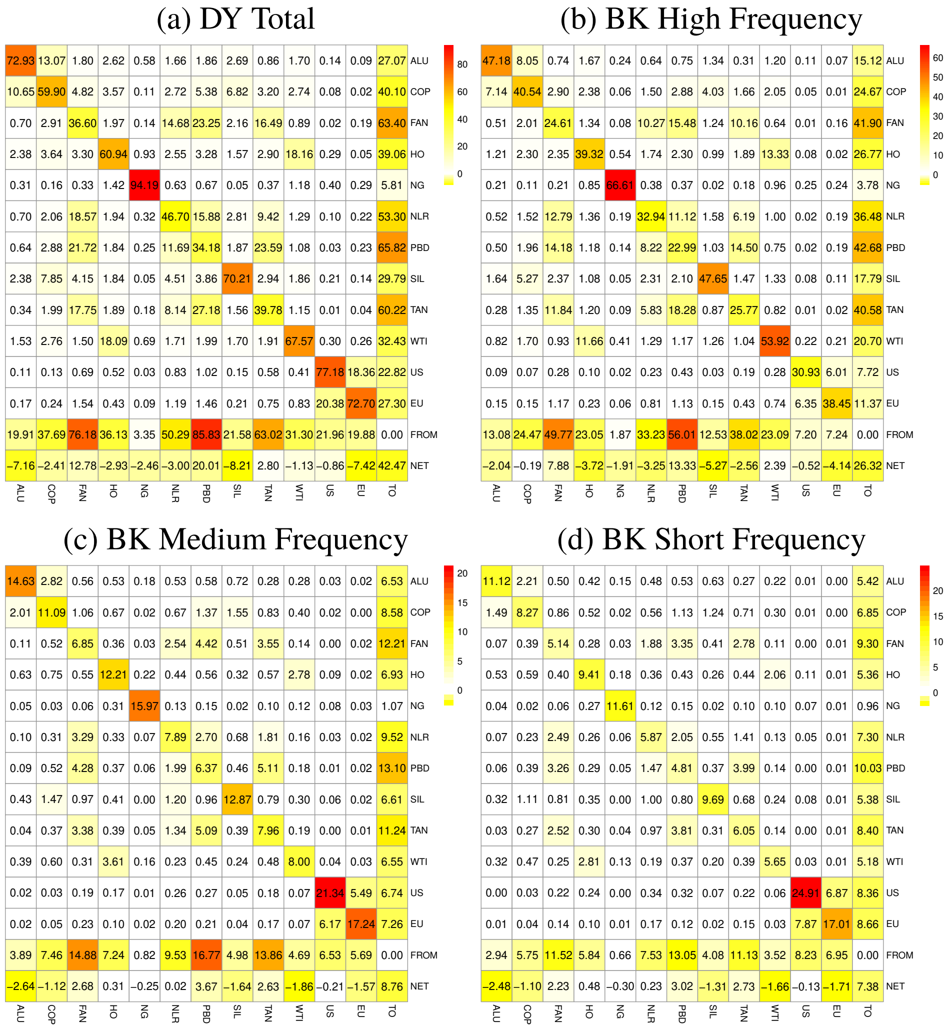


Figure 1.17: Spillovers on squared volatilities: DY and BK

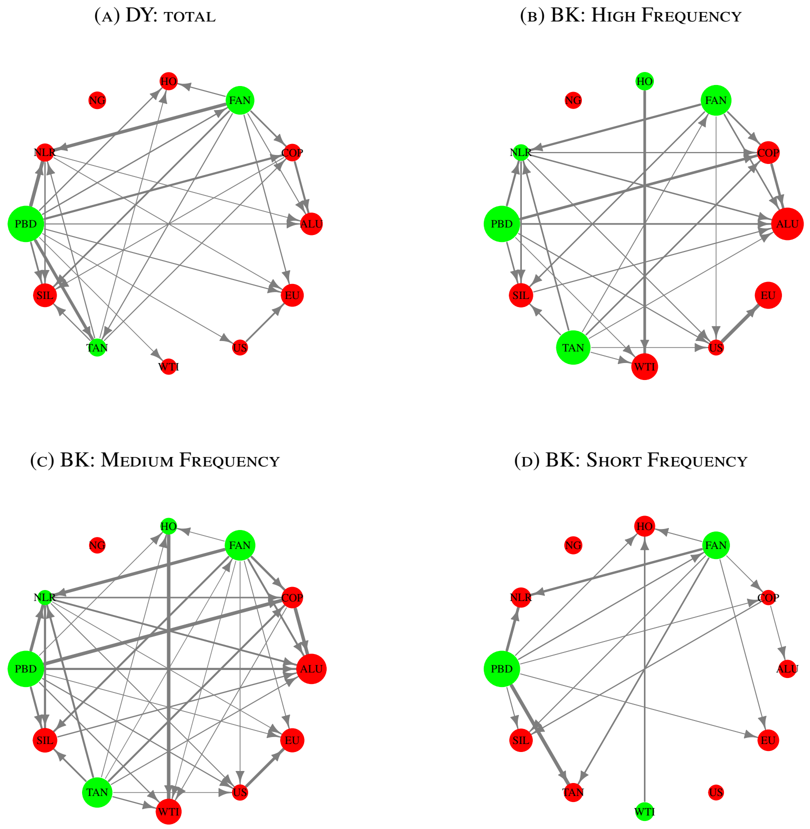


Figure 1.18: Network net volatility spillover on squared returns

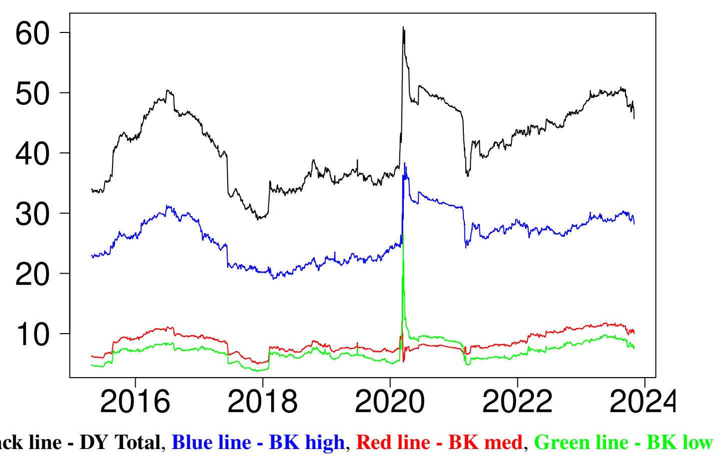


Figure 1.19: Dynamic TSI on squared volatilities.

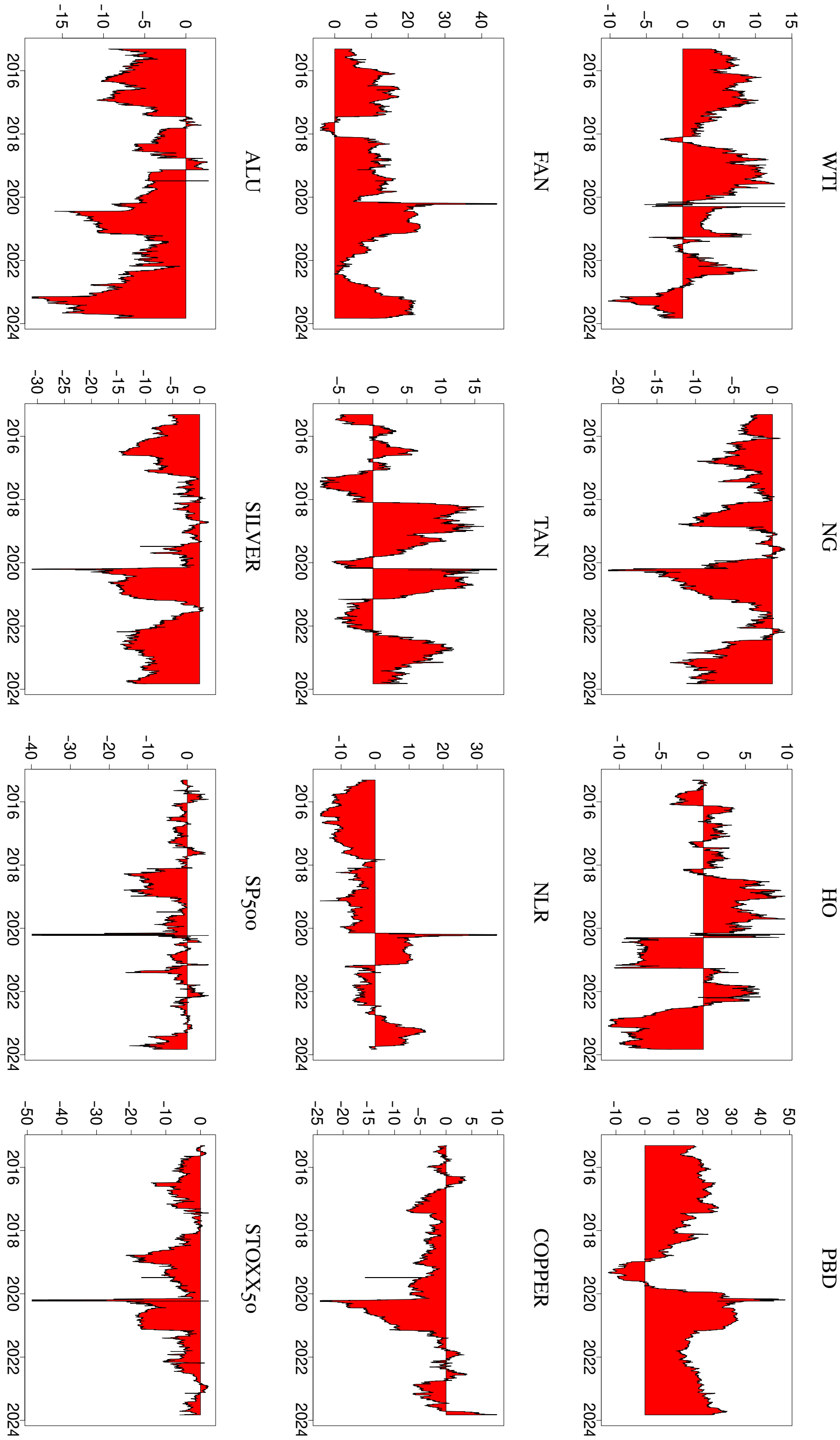


Figure 1.20: Diebold and Yilmaz (2012) Net Spillovers on squared returns

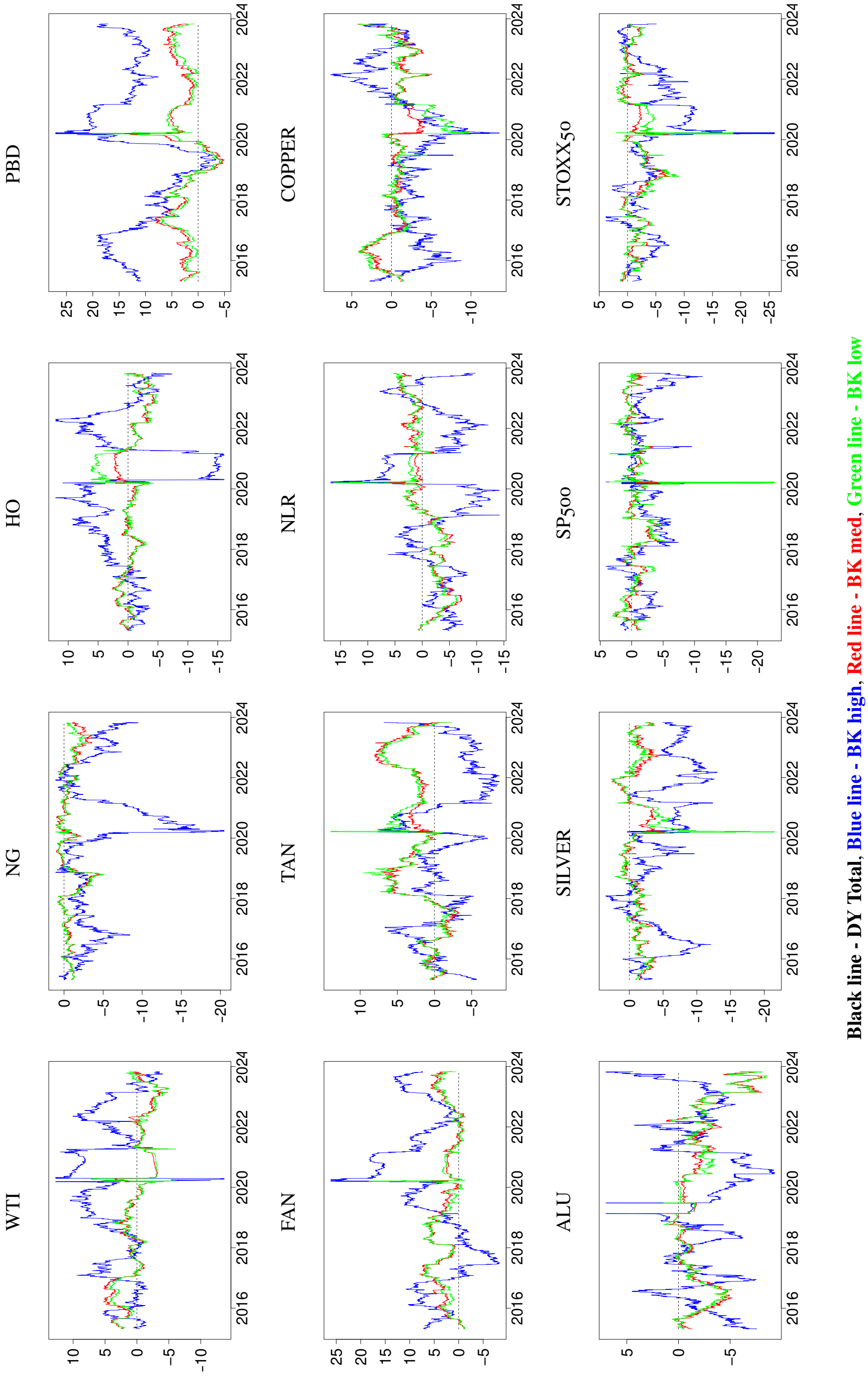


Figure 1.21: Baruník and Křehlík (2018) Net Spillovers on squared returns

Chapter 2

Energy consumption and economic growth in the decarbonization era. A panel data analysis

Abstract

This study investigates the relationship between energy consumption, economic growth, and environmental degradation in European countries from 1990 to 2022. We use a panel data estimator (Dynamic Common Correlated Effect Mean Groud, DCCEMG) to account for heterogeneity in the panel, unit root, and cointegration in the series dynamics, thus leading us to some relevant policy discussions. First, we highlight the significant role of renewable energy consumption in mitigating environmental degradation in Southern and Eastern European countries. Second, we report significant long(short)-term environmental benefits from using solar(wind) consumption. Interestingly, in Eastern European countries, we observe a negative impact of renewable energy consumption on economic growth given their poor renewable energy infrastructure development, aligning with the sustainable degrowth theory.

Keywords: Renewable Energy; CO2 Determinants; Degrowth theory; Causality

JEL Classification: C23, Q40

2.1 Introduction

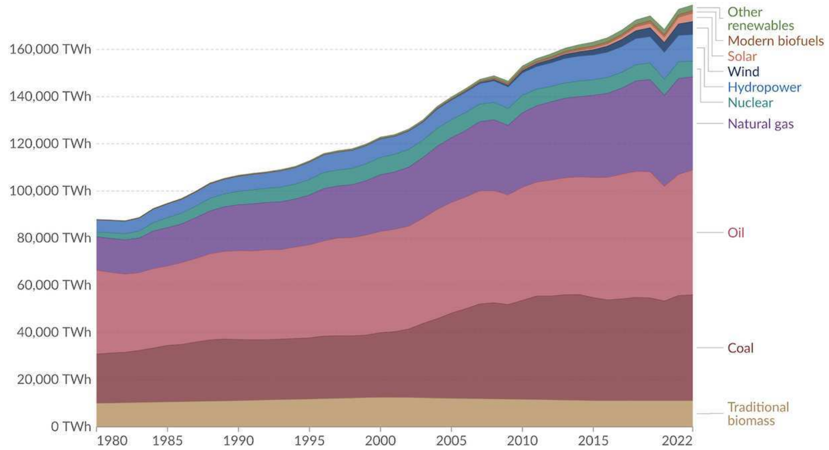
The relationship between energy consumption and economic growth has become the subject of intense debate in academic literature, especially after the Kyoto Protocol (1997) and the Paris Agreement (2015). The role of energy policies has been studied to understand whether they can influence global climate change. Many governments have sought to develop a transitional mechanism to promote more efficient and less polluting options that can simultaneously stimulate economic growth (Costantini and Martini, 2010). However, according to the "bioeconomic program" theory expressed in Georgescu-Roegen (1975), the economy might encounter a period of negative growth to downsize the economy and reduce the exhaustible resources used.[1]

The Georgescu-Roegen (1975) essay aligns with the Daly (1973) theory as the first broad example of a treaty on sustainable economics. In the literature on the energy transition, several studies have demonstrated the effectiveness of cleaner energies in reducing global pollution (see, for example, Panwar et al., 2011; Dincer and Acar, 2015; Paramati et al., 2022) that, however, are still a drop in the jar from a worldwide perspective, see Figure 2.1.

The role of Renewable Energy Sources (RES) depends closely on the relocation of the most polluting production from the richest to the developing countries that see environmental damage increase (Dasgupta et al., 2002; Capoani, 2023). Therefore, following Deshmukh et al. (2023), the development of RES is higher in developed countries that have had the opportunity not to make the burden of fossil energy consumption heavier.

The development of technology is crucial for a sustainable shift to cleaner energy. However, technological progress is different between industrialized and emerging countries. Indeed, Wang et al. (2019) show that in industrialized countries the positive effect of the development of sustainable sources is reflected in both production and consumption. In contrast, this effect is weak in developing countries (Lin et al., 2017). According to (Akram et al., 2021), developing countries should increase energy efficiency to stimulate technical progress. Adom et al. (2021) state how technological progress in poorer countries strongly depends on the levels of inequality

[1]The Club of Rome, an organization created to promote "sustainable growth", supported Georgescu-Roegen's idea.



Source: Energy Institute - Statistical Review of World Energy (2023) and ourworldindata.org

Figure 2.1: Global primary energy consumption by source

and the misalignment between energy supply and demand in the market.

The improvement and widespread adoption of RES can bring multiple benefits to countries from a climate and economic point of view. It allows national governments to improve their energy security by reducing dependence on imported energy and instead depending on domestically produced clean energy (Gozgor and Paramati, 2022). Following Balsalobre-Lorente et al. (2023), the shift to self-sufficiency in energy production can help mitigate the challenges associated with unstable energy prices, especially for nations heavily dependent on imports from other countries.

As emphasized by Khan et al. (2021a), energy consumption influences economic growth, thus increasing domestic production and affecting environmental degradation. Within this framework, Grossman and Krueger (1991, 1995), and Panayotou et al. (1993) introduced the Environmental Kuznets Curve (EKC) theory. The EKC hypothesis illustrates an inverted U-shaped relationship between income (x-axis) and environmental degradation (y-axis). According to the existing literature, some analyses confirm the inverted U-shaped curve (Farhani et al., 2014; Ridzuan, 2019; Ahmad et al., 2021; Arshad Ansari et al., 2020), while other reject the EKC hypothesis (Harbaugh et al., 2002; Menegaki, 2011a; Pontarollo and Mendieta Muñoz, 2020; Ridzuan et al., 2020, see also Table 2.11 in Appendix 2.A, where we report a more detailed explanation of this theory).

The EKC hypothesis is a controversial topic that has been questioned in the academic literature. First, following Arrow et al. (1995) and Stern et al. (1996), the validity of the EKC strictly depends on the effects of trade on the distribution of polluting industries. In this sense, Dasgupta et al. (2002) introduced the "race to the bottom" scenario, in which industries in developed countries apply a sort of relocation to developing countries, thus making their environmental burden heavier. Furthermore, as Stern (2004) highlights, the role of control variables (if not motivated) is quite relevant in this debate. On this line, Luzzati and Orsini (2009) argue that the choice of the subsample is fundamental to validate the EKC. Given these considerations, we use economic growth among the CO2 determinants, but we do not have the aim to test the validity of the EKC.

As evident, energy consumption and economic growth are closely connected. Many scholars attempt to study the contribution of energy consumption to economic development. Mehrara (2007) introduced four hypotheses based on the causality between economic growth and energy consumption (see Table 2.1). For instance, Bhattacharya et al. (2016a), Zafar et al. (2019) and Le et al. (2020), confirm the growth hypothesis while Bento and Moutinho (2016), Destek and Aslan (2017) and Mbarek et al. (2018), find several elements in favor of the feedback hypothesis.

Growth hypothesis	It suggests that there is *one-way causality* from energy consumption to economic growth. According to Payne (2010), the growth hypothesis supports the view that conservation-oriented policies have a lower impact on economic growth
Conservation hypothesis	The opposite of the growth hypothesis since an increase in real GDP provokes a *one-way rise* in energy consumption. According to this hypothesis, conservation policies, such as the GreenHouse Gas (GHG) reduction and energy efficiency enhancement guidelines, would not impact economic growth. Payne (2010) affirmed that in a prosperity economics period, political, infrastructural, or resource mismanagement could generate inefficiencies and a reduction in the demand for goods and services, including energy consumption. In this case, an increase in real GDP might harm energy consumption
Feedback hypothesis	This suggests that energy consumption and economic growth are interdependent and supplementary. In this case, any increase (decrease) in energy consumption results in an increase (decrease) in GDP and vice-versa.
Neutrality hypothesis	There is no causality between energy consumption and GDP. Therefore, neither a conservative energy policy nor an energy expansion policy, has any effect on economic growth.

Table 2.1: Classic causality hypothesis

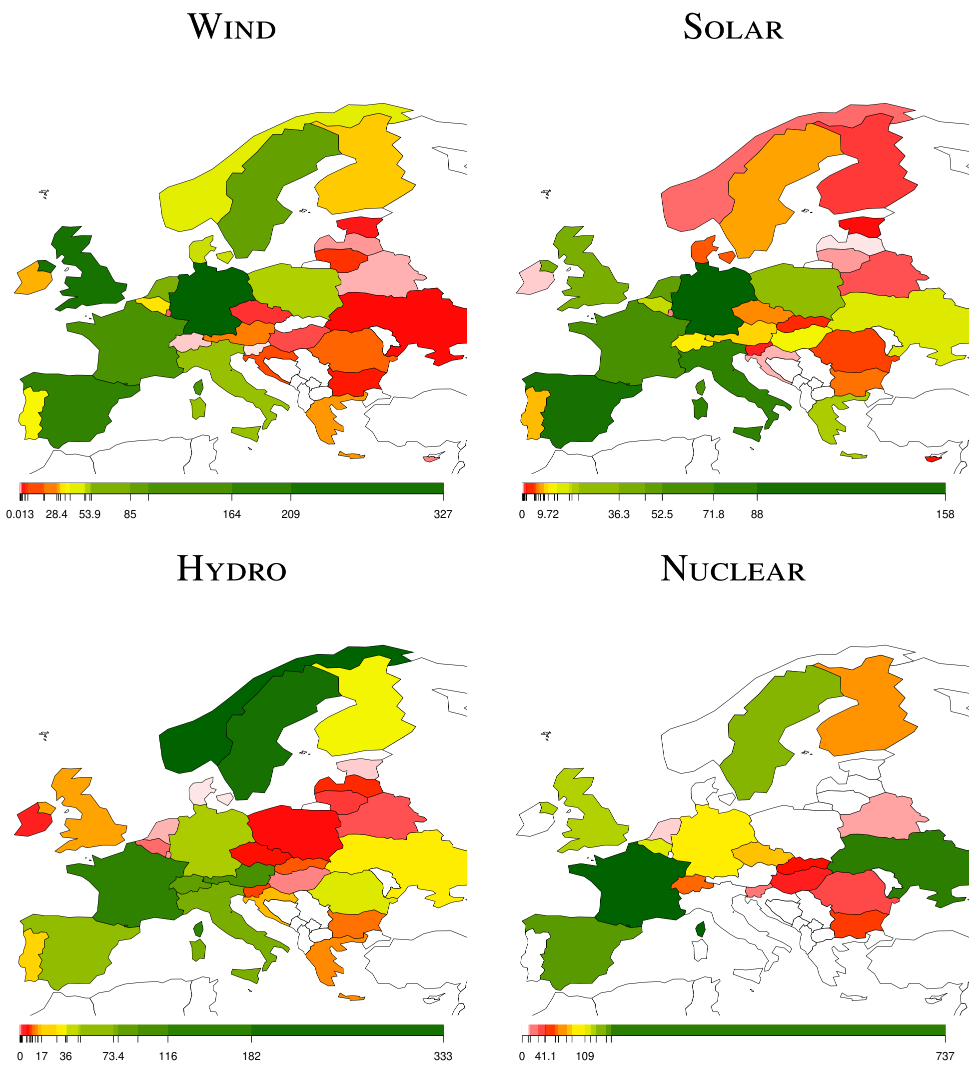
We aim to fill the literature gap in several ways. First, while several studies used a panel of heterogeneous countries (see, for example Jebli and Youssef, 2015; Ivanovski et al., 2021; Namahoro et al., 2021), we examine a panel composed of countries from the same geographical area, Europe. In particular, we distinguish from Simionescu (2021) and Simionescu et al. (2022) by expanding the sample to Northern European countries and including slope heterogeneity, cross-sectional dependence, and cointegration in our analysis, also considering the effect of environmental policies. We improve the work of Frodyma et al. (2022) by using an aggregate measure of carbon dioxide emissions. To the best of our knowledge, we are the first to deal with all these issues around the European economies.

Second, we divide renewable/clean energy consumption into subgroups: hydroelectric, nuclear, solar, and wind. Accordingly, given the high differences in renewable energy consumption sources in the EU (see Figure 2.2), understanding the effect of different renewable energy sources on environmental degradation could improve the definition of policies. Within this context, we investigate the role of economic growth on specific renewable energy consumption and vice versa to comprehend whether some patterns emerge.

Third, differently from Marra and Colantonio (2021) and Hassan et al. (2024), we include the Environmental Policy Stringency (EPS) index to investigate its country-by-country impact on renewable energy and economic growth. To conclude, we extend the sample after the Covid-19 period and the Russian invasion of Ukraine, thus considering the recent decarbonization era.

Among the determinants of CO2, we find a non-linear relationship with economic growth, proxied by the per capita GDP. Renewable energy consumption reduces economic growth in some Eastern European countries. Based on the degrowth theory, we align with the “sustainable decrease hypothesis”. Additionally, the negative impact of environmental policies on economic growth and renewable consumption in Eastern Nations is emphasized.

The rest of the Chapter is divided as follows. Section 2.2 provides an extensive literature review, while Section 2.3 explains the methodology and introduces the dataset. Section 2.4 discusses the result and Section 2.5 concludes.



Note: All the values are measured in terawatt-hours. White: no data.

Figure 2.2: Renewable energy sources consumption (2022)

2.2 Literature review

Given the demonstrated empirical relationship between economic growth and energy consumption (both renewable and fossil), energy policies are becoming essential to guarantee a sustainable development path (Dasgupta et al., 2002). The Kyoto Protocol (1995) developed the first joint global action to ensure fixed pollution degree to guarantee sustainable development. The Paris Agreement (2015) strived to restrict global average temperature rise.

Part of the literature investigated the causality between energy consumption and

GDP growth, often used as a proxy for wealth. Scholars focused on the four causal hypotheses discussed in Table 2.1. Tiba and Omri (2017) published a general literature review of this topic, dividing the work into two fields: the causality between energy consumption/production and the nexus among economic growth, environment, and production. They report mixed and contradictory results. The main reason resides in the methodology used and the omitted variable bias, as also discussed in Luzzati et al. (2018) and Armeanu et al. (2018); it occurs when the analysis does not consider one or more relevant variables.

Given the growing interest in renewable energies, literature has begun to study its role in economic growth. Sustainable economic development is one of the main factors that governments consider when formulating energy policies (Stiglitz, 2017). The effect of renewable energy consumption on wealth levels strictly depends on the country's characteristics (such as social awareness and green policies). Bhattacharya et al. (2016b) find a positive effect of renewable energy consumption on economic growth for 57% of countries in a sample of 38 nations. Tugcu et al. (2012) reach a contrasting result for the panel of G7 countries. Inglesi-Lotz (2016a) discover a positive statistical significance of renewable energy consumption on economic growth, thus suggesting that promoting environmentally friendly energy stimulates economic conditions.

Menegaki (2011a) analyzes the relationship between renewable energy and GDP in Europe, finding no significant effects. Alper and Oguz (2016a) investigates the link between economic growth and renewable energy in Eastern European countries, reporting a positive relationship. Cho et al. (2015) argue that the impact of renewable energy sources on the economy is closely linked to the structural development of countries, suggesting considering the level of industrialization. Therefore, to study the role of the degrowth hypothesis, we also believe that the degree of renewable energy development in the country is crucial to explain the differences across countries.

2.2.1 Causality analysis

The first set of analyses based on a Fully Modified OLS (FMOLS) and an Autoregressive Distributed Lags (ARDL) approach show the validity of the feedback hypothesis (Apergis and Payne, 2010a,b, 2011, 2012; Apergis and Tang, 2013; Pao and Fu, 2013). Apergis and Payne (2010a) study a sample of Eurasian countries from 1992 to 2007. Apergis and Payne (2010b) conduct a panel data analysis based on 20 OECD countries from 1985 to 2005 studying non renewable energy consumption behavior. The same period is analyzed by Apergis and Payne (2011), which examine the performance of renewable energy consumption in six US countries. According to Pao and Fu (2013), economic growth plays a relevant role in fostering the development of the renewable sector. The same study reported the unidirectional causality between non-hydro renewable energy consumption and economic growth. In addition, they prove a bidirectional causality between economic growth and total renewable energy consumption.

Destek and Aslan (2017) confirm the feedback hypothesis using a panel bootstrap causality analysis on emerging economies between 1980 and 2012. In addition, the results show that renewable energy consumption stimulates economic growth in Peru, Greece, and South Korea. Quite the opposite, Non-Renewable Energy Consumption develops the economy in China, Colombia, Mexico, the Philippines, and Turkey. Mbarek et al. (2018) obtain the same result in France, Italy, Spain, and Turkey (Bento and Moutinho, 2016, confirm the feedback hypothesis for Italy). In addition, Sebri and Ben-Salha (2014) and Kahia et al. (2016) conduct a VECM analysis, the former on the BRICS countries from 1971 to 2010 and the latter on the Middle East and North Africa (MENA) oil-exporting countries from 1980 to 2012, again confirming the feedback hypothesis. For the BRICS countries, the results were confirmed by Shahbaz et al. (2016).

Lin and Moubarak (2014) find the feedback hypothesis for China from 1977 to 2011. In addition, the results of Alper and Oguz (2016b) and Saad and Taleb (2018) show the validity of the feedback hypothesis for a sample of EU member countries in the periods 1990-2009 and 1990-2014, respectively, using ARDL and VECM causality methods. The feedback hypothesis is also confirmed by Narayan and Doytch

(2017), who analyzed a sample of 89 countries from 1971 to 2011 using the Generalized Method of Moments (GMM) and fixed-effects (FE) estimates. Furthermore, according to Sun et al. (2020), and Sebri and Ben-Salha (2014) respectively, bidirectional causality between energy consumption and economic growth emerge for a panel of OECD and B&R (Belt & Road) countries from 1992 to 2015 and for BRICS countries from 1971 to 2010.

One of the widely used techniques in the literature to identify causality is the Toda-Yamamoto procedure. On this line, Bowden and Payne (2010) and Fang (2011) support the growth hypothesis for the United States and China. The ARDL technique led Amri (2017) to conclude about the boost in the economic growth led by the rise in renewable sources for Algeria between 1980 and 2012. Bilgili (2015) studies the relationship between renewable energy and economic growth in the US using a wavelet (partial) coherence analyses, finding a relevant role of industrial production.

Bhattacharya et al. (2016a) analyze the nexus between economic growth and energy consumption. They confirm the growth hypothesis for non renewable energies and the neutrality relationship for renewables systems for a sample made by 38 countries from 1991 to 2012. Le et al. (2020) apply a Feasible Generalised Least Square (FGLS) technique to identify the causal relationship between energy consumption and economic growth in 102 countries, finding elements supporting the growth hypothesis. These achievements are confirmed by Zafar et al. (2019), who perform the same econometric method on 16 Asia-Pacific countries from 1995 to 2015.

Menegaki (2011b) employs the Dynamic Error Correction Model (DECM) to examine the nexus between renewable energy and economic growth in European countries from 1997 to 2007. She supports the neutrality hypothesis since no relationship between renewable energy and economic growth emerged. The neutrality hypothesis was confirmed also by Jebli and Youssef (2015) and Adams et al. (2018). The first selected a sample of 69 countries from 1980 to 2010 and employed FMOLS and OLS with Granger causality analysis. Adams et al. (2018) analyze the behavior of renewable energy consumption in 30 Sub-Saharan African countries (1980-2012) using the Dumitrescu-Hurlin causality. According to Ivanovski et al. (2021), the impact of renewable energy consumption on economic growth is statistically indistinguishable from zero in OECD countries from 1990 to 2015, while renewable energy promotes energy growth in non-OECD countries.[2]

The literature does not convey the validity of the conservation hypothesis. However, (Sadorsky, 2009a,b) demonstrate how increasing GDP per capita is one driver of renewable energy consumption. This result is strongly related to the characteristics of the countries analyzed. For example, Furuoka (2017) conducts a Dumitrescu-Hurlin causality test for a sample of Baltic countries (Estonia, Latvia, and Lithuania), investigating the link between renewables and growth between 1992-2011. The author has provided a comprehensive literature review organized in tabular form that can be a reference for the reader. The findings suggest that governments in the Baltic countries are free to implement conservation policies without hindering economic development. Rahman and Velayutham (2020) confirm this relationship for a sample of 5 South Asian countries

Fewer analyses focused on individual countries. Ocal and Aslan (2013) examine the economic growth-renewable energy nexus for Turkey, Azlina et al. (2014) for Malaysia, and Brini et al. (2017) for Tunisia. The former found a negative impact of renewable energy consumption on economic growth from an ARDL analysis, confirming the validity of the conservation hypothesis. Azlina et al. (2014) reveal a Granger causality nexus from income to energy consumption and renewable energy use. In conclusion, Brini et al. (2017) analyze through an ARDL approach the situation in Tunisia for a time frame 1980-2011, supporting the conservation hypothesis.

There is also a field in the literature focusing on the cauality between Carbon Emmissions and Renewable Energy Consumption which we summarize in Table 2.2.

Authors	**Methodology**	**Variables**	**Controls**	**Periods**	**Sample**	**Results**
Sadorsky (2009b)	Pedroni, FMOLS, DOLS	REC, CE	GDP, OP, CO_2	1980-2005	G7	CE $\rightarrow$ REC
Apergis et al. (2010)	Panel ECM, GC	REC, NE	GDP, NE	1984-2007	19 develop.	CE $\rightarrow$ REC
Menyah and Wolde-Rufael (2010)	Toda-Yamamoto, GC	REC, NE	NE, GDP, EPI	1960-2007	US	CE $\rightarrow$ NE

[2] For a more exhaustive review of causality between non-renewable energy consumption and economic growth see Adedoyin et al. (2020).

Tiwari (2011)	SVAR model	REC, CE	GDP, CE	1960-2009	India	REC → CE
Payne (2012)	Toda-Yamamoto	REC	GDP, OP, CE	1949-2009	US	REC ≠ CE
Apergis and Payne (2014)	FMOLS, Panel causality	REC	GDP, OP, CP	1980-2010	7 American	REC → CE
Shafiei and Salim (2014)	STIRPAT model, AMG, Panel GC	REC	POP, URB, EI, nREC, SIS	1980-2011	OECD	CE → REC
Sebri and Ben-Salha (2014)	VECM	REC	GDP, TO, CE	1971-2010	BRICS	CE → REC
Jaforullah and King (2015)	Johansen, VECM	CE	GDP, EPI, NE	1965-2012	US	REC → CE
Al-Mulali and Ozturk (2016)	Kao Coint., FMOLS, GC	REC	GDP, nREC, TO, URB, EI	1990-2012	27 develop.	REC → CE
Dogan and Seker (2016)	DOLS, DH	REC	GDP, TO	1980-2012	EU	REC ↔ CE
Bilgili et al. (2016)	Pedroni, FMOLS, DOLS	REC,CE	GDP	1977-2010	17 OECD	REC → CE
Bento and Moutinho (2016)	ARDL, Toda-Yamamoto	REC	CE, GDP, IT	1960-2011	Italy	REC ↔ CE
Jebli et al. (2016)	Pedroni, FMOLS, DOLS/VECM	REC,CE	GDP, nREC, IT	1980-2010	OECD	REC ↔ CE
Mbarek et al. (2018)	Pedroni, Kao, VECM	REC	GDP, CO_2	1980-2012	South EU	CE → REC
Inglesi-Lotz and Dogan (2018)	Long Panel, DH	REC	GDP, TO	1980-2011	Sub-Saharan	CE → REC
Hu et al. (2018)	FMOLS, DOLS	REC	GDP, TO	1996-2012	25 developing	REC ↔ CE
Nguyen and Kakinaka (2019)	Pedroni, FMOLS, DOLS	REC	GDP, OP, CE	1990-2013	107 countries	REC → CE

Destek and Aslan (2020)	AMG, Panel bootstrap causality	REC	GDP, CE	1991-2014	G7	REC $\rightarrow$ CE
Adedoyin et al. (2020)	PMG, DARDL	REC	NE, GDP, RQ, CO_2	1990-2014	BRICS	REC $\rightarrow$ CE
Saidi and Omri (2020)	FMOLS, VECM	REC,CE	GDP, URB, CO_2, LF	1990-2014	15 count.	REC $\leftrightarrow$ CE (*short-run*)
Ahmad et al. (2021)	Westerlund, DH	REC	GDP, TO, FDI	1990-2014	OECD	REC $\leftrightarrow$ CE

Table 2.2: Main Literature

Note: Renewable Energy Consumption (REC) and Carbon Emission (CE) defined based on Smyth and Narayan (2015) and Sarkodie and Strezov (2019). GDP: Real Gross Domestic Product, OP: Real Oil Price, NE: Nuclear Energy, EPI: Energy Price Index, CP: Real Coal Price, EI: Energy intensity, TO: Trade Openess, SIS: Share of industry and services, LF: Labor force, NUC:Nuclear, IT: International Trade, RQ: Regulatory Quality, DH: Dumitrescu-Hurlin, AMG: augmented mean group estimator, GC:Granger Causality; $\rightarrow$ Unidirectional GC from x to y; $\leftarrow$ Unidirectional GC from y to x; $\leftrightarrow$ Bidirectional GC from x to y.

2.2.2 Environmental Kuznets Curve

At the nexus between energy consumption and economic growth, the Environmental Kuztnes curve (EKC) is an extremely popular theory among scholars.[3] In particular, let suppose that environmental degradation and economic growth are linked by the following equation

$$\text{ED} = \beta_0 + \beta_1 \text{GDP} + \beta_2 \text{GDP}^2 + e_t \tag{2.1}$$

where ED is the Environmental Degradation, GDP is the Gross Domestic Product and e_t is the disturbance term. Typically, the literature tests if $\beta_1 < 0$ and $\beta_2 > 0$ to conclude about the EKC validity.

In many empirical works, Equation (2.1) is augmented by a set of control variables to mitigate the omitted variable bias discussed in Stern (2004). With the additional consideration of a set of control variables into the equation, researchers study the determinants of CO2 rather than the validity of the EKC. Given the contrasting results

[3]The name EKC was taken from Kuztnes (1955) who stated that income inequality and economic development were linked by a non-linear relationship (first it increases and then decreases).

(see Table 2.11), the choice of ad hoc control variables could lead to the EKC validity as also reported in Kaufmann et al. (1998) and Itkonen (2012).

For example, including some controls, an inverted U-shape between income and environmental quality is found in Shahbaz et al. (2015b) for a subset of high-, middle-, and low-income countries, while Orubu and Omotor (2011) confirmed the validity of the EKC for an African panel. Furthermore, Ozturk and Acaravci (2010) showed how the EKC was not valid for Turkey in the period 1968-2005, while Al-Mulali et al. (2015) established the inverted U-shaped relationship between environmental degradation and GDP for Vietnam from 1981 to 2011.

The country-by-country investigation produced mixed results. According to Bouznit and Pablo-Romero (2016) Sinha and Shahbaz (2018), Mrabet and Alsamara (2017), Nnaji et al. (2013) and Shahbaz et al. (2015a), the EKC theory applied for Algeria (1970-2010), India (1971-2015), Qatar (1980-2011), Nigeria (1971-2009) and Portugal (1971-2008), respectively. Asian countries such as Pakistan and China have been heavily analyzed (see, for instance, Mirza and Kanwal, 2017; Sharif et al., 2017; Koondhar et al., 2020; Yuan et al., 2015), partially demonstrating on average the existence of the EKC curve.

Saint Akadırı et al. (2021) tested the EKC for BRICS countries, finding statistical evidence of the long-run inverted U-shaped relationship between economic growth and environmental degradation. BRICS countries have been strongly studied because they are a group of comparable countries (Balsalobre-Lorente et al., 2019; Haseeb et al., 2018, confirm the EKC). The EKC hypothesis was tested and validated for a sample of Sub-Saharan African countries (Sarkodie, 2018). Bibi and Jamil (2021) study the EKC for six different regions, including Latin America and the Caribbean, East Asia and the Pacific, Europe and Central Asia, South Asia, the Middle East and North Africa, and sub-Saharan Africa, during the period from 2000 to 2018. They find statistical evidence for EKC in the entire panel, except for sub-Saharan Africa.

As we saw, scholar focused on different countries and try to validate the EKC hypothesis considering different controls and based on the analysed sample. Indeed, Balado-Naves et al. (2018) conducted a regional study finding that the role of neighbouring per capita income and national per capita emissions is crucial to validate the

EKC hypothesis.[4]

2.2.3 Control Variables

In the context of CO2 determinants, the choice of control variables is fundamental to limit the endogenous estimation since the omitted variable problem could affect the energy-growth nexus. Several authors, such as Camarero et al. (2015), declare the entire energy-growth nexus framework questionable due to econometric weakness and theoretical inconsistencies. In general, we could try to mitigate the bias by employing the available variables based on economic theory. According to Westerlund et al. (2015), a robust set of control variables should be employed to reduce the bias, but there is no agreement in the literature on the specific control variables. The general analysis of Apergis and Tang (2013) concludes that three or more variables can mitigate the coefficient estimation bias. This correction ensures the robustness of the results.

Sadorsky (2006) use the oil price as the additional variable for a sample of G7 countries to determine the relationship between renewables and carbon emissions. According to Shafiei and Salim (2014), the urban population and the share of industry and services in the whole industrial set are essential to mitigate the problem of omitted variables.

Urban population is one of the most frequently used variables in this framework (Sebri and Ben-Salha, 2014; Al-Mulali and Ozturk, 2016; Wang and Zhang, 2020) together with tarde openness (Shafiei and Salim, 2014; Al-Mulali and Ozturk, 2016; Dogan and Seker, 2016; Bento and Moutinho, 2016; Inglesi-Lotz, 2016b). In general, other common controls in this context are: labor force (Wen and Dai, 2021; Bilgili et al., 2023), primary energy consumption (Valadkhani et al., 2019; Bekun et al., 2021) and coal consumption Altıntaş and Kassouri (2020); Jonek-Kowalska (2022). To align with this literature we include these variables in our analysis.

[4] see Table 2.11 and Pata and Aydin (2020); Pata and Caglar (2021) for a more detailed review.

2.3 Metodology and Data

2.3.1 Methodology

Given the enormous amount of data on energy consumption and economic determinants, we have tried to collect as much data as possible in the context of European countries. Therefore, we need a panel data estimator dealing with a long time series component and a cross-sectional dimension. Consequently, we use the Dynamic Common Correlated Effect Mean Group (DCCEMG) estimator of Chudik and Pesaran (2015).[5] In particular, the DCCEMG estimator allows us to account for the cross-sectional dependence between panel data and the non-stationarity of the variables, thus modeling the potential cointegration relationship. We specify the model according to Chudik et al. (2016) via a CS-ARDL (Cross-Sectional AutoRegressive Distributed Lags) specification to calculate the short-run and long-run coefficients.

Before proceeding with the estimations, we need to check the validity of statistical assumptions through the usage of specific tests:

1. Slope heterogeneity test: it aims to test if slope coefficients are heterogeneous in the cross-sectional dimension.
2. Cross-sectional dependence test: it assesses the potential correlation between error terms across different cross-sectional units.
3. Unit Root test: it determines whether the variables exhibit a unit root.
4. Cointegration test: it investigates whether there exists a long-run relationship between the variables.

Slope heterogenity

According to Pesaran and Smith (1995), especially when the time series dimension (T) is high, the slope heterogeneity might bias the results. Baltagi (2008) proposed to apply an F-type test on the difference of the sum of squared residuals from pooled ordinary least squares and cross-section unit-specific OLS to test slope homogeneity. Bun (2004) demonstrated that when $T > N$ (with N cross-sectional units), this test

[5] It is the dynamic version of the work Pesaran (2006).

has a good performance. Pesaran et al. (1996) introduced a Hausman-type test when $N > T$ compares the Fixed Effects (FE) estimator and cross-section unit-specific OLS. However, according to Pesaran and Yamagata (2008), the procedure does not apply to models with only strictly exogenous regressors or autoregressive components.

According to Pesaran and Yamagata (2008), the slope homogeneity test is a standardized version of Swamy (1970) test. Consider the panel data model with two regressors

$$y_{it} = \alpha_i + x'_{1,it}\beta_{1i} + x'_{2,it}\beta_{2i} + \varepsilon_{it} \tag{2.2}$$

where $i = 1, \ldots, N$, $t = 1, \ldots, T$, and β_{1i} and β_{2i} are $k_1 \times 1$ and $k_2 \times 1$ vectors of slope coefficients, with $k = k_1 + k_2$. In this case, the hypothesis system is

$$\begin{cases} H_0 : \beta_{21} = \beta_{22} = \cdots = \beta_{2n}, \\ H_1 : \beta_{2i} \neq \beta_{2j}, \text{ for some } i \neq j. \end{cases} \tag{2.2H}$$

Since $x_{2,it}$ vector contains strictly exogenous regressors, the coefficients in β_{2i} are tested for slope homogeneity. The test statistic is

$$\Delta = \frac{1}{\sqrt{N}}\left(\frac{\tilde{S}_2 - k_2}{\sqrt{2k}}\right), \tag{2.3}$$

where, under the H_0, it is asymptotically distributed as a standardized normal distribution. $\tilde{S}_2$ is defined as

$$\tilde{S}_2 = \sum_{i=1}^{N}(\hat{\beta}_{2i} - \hat{\beta}_{2,FE})' \frac{(x'_{2i}\mathbf{M}_{1i}x_{2i})}{\sigma_i^2}(\hat{\beta}_{2i} - \hat{\beta}_{2,FE}), \tag{2.4}$$

with $\hat{\beta}_{2i}$ and $\hat{\beta}_{2,FE}$ are the estimate of β_{2i} respectively from the individual OLS estimation and a Fixed Effect (FE) model. $\mathbf{M}_{1i} = I_T - z_{1,it}(z'_{1,it}z_{1,it})^{-1}z_{1,it}$ is the projection matrix which include the regressors that are not of interest (the constant and $x_{1,it}$). The σ_i^2 is

$$\sigma_i^2 = \frac{(y - x'_{2,it}\beta_{2,FE})'\mathbf{M}_{1i}(y - x'_{2,it}\beta_{2,FE})}{T-1}.$$

Using bias adjusted $\tilde{\Delta}$ test may lead to robust findings to increase the properties of the small samples. $\tilde{\Delta}$ is described as follows

$$\tilde{\Delta} = \frac{\sqrt{N}}{\sqrt{\Xi}} \left(\frac{1}{N} \tilde{S}_2 - k_2 \right) \tag{2.5}$$

where

$$\Xi = \frac{2k_2(T_i - k - 1)}{T_i - k - 1}$$

Since the Pesaran and Yamagata (2008) test is based on the homoskedasticity and no serial correlation assumption, Blomquist and Westerlund (2013) defined an alternative test which takes into account these two features. To avoid that autocorrelation in errors, the Blomquist and Westerlund (2013) test is based on the HAC version

$$\Delta_{HAC} = \sqrt{N} \frac{\left(N^{-1} \tilde{S}_{HAC} - k_2 \right)}{\sqrt{2k_2}} \tag{2.6}$$

$$\text{with} \quad \tilde{S}_{HAC} = \sum_{i=1}^{N} T_i (\hat{\beta}_{2i} - \hat{\beta}_{2,HAC})' (\hat{\mathbf{Q}}'_{it_i} \hat{\mathbf{V}}_{it_i}^{-1} \hat{\mathbf{Q}}_{it_i}) (\hat{\beta}_{2i} - \hat{\beta}_{2,HAC}),$$

where $\hat{\mathbf{Q}}_{\mathbf{it}}$ is a projection matrix to bias the heterogeneous variables

$$\hat{\mathbf{Q}}_{\mathbf{it}} = \frac{1}{T_i} (x'_{2i} \mathbf{M}_{1i} x_{2i}),$$

and $\hat{\beta}_{2,HAC}$ is a robust HAC estimator of the pooled β_2 coefficients

$$\hat{\beta}_{2,HAC} = \left(\sum_{i=1}^{N} T_i \hat{\mathbf{Q}}_{it_i} \hat{\mathbf{V}}_{it_i}^{-1} \hat{\mathbf{Q}}_{it_i} \right)^{-1} \sum_{i=1}^{N} \hat{\mathbf{Q}}_{it_i} \hat{\mathbf{V}}_{it_i}^{-1} x'_{2i} \mathbf{M}_{1i} y_i.$$

The $\hat{\mathbf{V}}_{\mathbf{it}}$ matrix is the HAC correction

$$\hat{\mathbf{V}}_{\mathbf{it}} = \mathbf{B}_i(0) \sum_{t=j}^{T_i - 1} Ke \left(\frac{j}{Band_{iT_i}} \right) [\mathbf{B}_i(j) + \mathbf{B}'_i] \tag{2.7}$$

with $\mathbf{B}_i = \frac{1}{T_i} \sum_{t=j+1}^{T_i - 1} \hat{u}_{it} \hat{u}'_{it-j}$, $\hat{u} = (\tilde{x}_{2,it} - \tilde{\bar{x}}_{2,it}) \hat{\varepsilon}_{it}$, $\tilde{\bar{x}}_{2,it} = \frac{1}{T_i} \sum_{t=1}^{T_i} \tilde{x}_{2,it}$, where $\tilde{x}_{2,it}$ is the t-th element of $x_{2,it} \mathbf{M}_{1i}$. $\hat{\varepsilon}_{it}$ is the estimated residual from FE model, Ke is the kernel function, and $Band$ is the bandwidth parameter. To account for cross-sectional dependence the model is expressed with a common factor structure. The difference from previous tests is based on the cross-sectional averages of $y_{it}, x_{1,it}$ and $x_{2,it}$ to eliminate the strong cross-sectional dependence.

Cross Sectional dependence

Since we experienced an increasing economic and financial integration of countries and financial entities, the interdependencies between cross-sectional units steadily rose. As a consequence, the panel-data literature (See, among others, Robertson and Symons, 2000; Anselin, 2003; Pesaran, 2004) concludes that panel estimations reveal substantial cross-sectional dependence in the errors. The cross-sectional dependence may arise from common shocks, unobserved components, spatial dependence, and idiosyncratic errors pairwise dependence.

According to Chudik et al. (2011), the literature differentiates the weak and strong cross-sectional dependence. The weak cross-sectional dependence is accounted employing spatial methods. Conversely, the strong cross-sectional dependence is modeled via common time-specific factors and loadings. We refer to strong (or strict) cross-sectional dependence.

To address the cross-sectional dependence problem, the Pesaran (2004) (CD) test has typically been used. This test is an investigation of the average correlation between panel units. The intuition is about the transformation of the sum of pairwise correlations between panel units that are normally distributed. The null hypothesis is strict cross-sectional independence. Consider the generalization of Equation 2.2

$$y_{it} = \alpha_i + x'_{it}\beta + e_{it} \tag{2.8}$$

with $i = 1, \ldots, N$, $t = 1, \ldots, T$, α_i is the time-invariant individual nuisance parameter, x_{it} is a $k \times 1$ vector of regressors and β is a $k \times 1$ vector of parameters to estimate. Under the null hypothesis, the e_{it} is assumed to be iid over periods and across cross-sectional units (no cross-sectional dependence). Thus, the hypothesis is

$$\begin{cases} H_0 : \rho_{ij} = \rho_{ji} = corr(\varepsilon_{it}, \varepsilon_{jt}) = 0, \text{ for } i \neq j \\ H_1 : \rho_{ij} = \rho_{ji} \neq 0, \text{ for some } i \neq j. \end{cases} \tag{2.9H}$$

where ρ is the product-moment correlation coefficient of the errors

$$\rho_{ij} = \rho_{ji} = \frac{\sum_{t=1}^{T} e_{it}e_{jt}}{\sqrt{\left(\sum_{t=1}^{T} e_{it}^2 e_{jt}^2\right)}} \tag{2.9}$$

The CD test resembles the Breusch and Pagan (1980) test (BP), generalized as the LM test

$$LM = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij}^2 \tag{2.10}$$

where, $\hat{\rho}$ is the estimated product-moment correlation coefficient of the errors in Equation (2.9). The LM statistic is asymptotically distributed as a χ^2 with $N(N-1)/2$ degree of freedom. Pesaran (2004) introduced the CD test because the LM is likely to exhibit substantial size distortions when N is large and T is finite. The CD test statistic for balanced panel is

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{\rho}_{ij} \right). \tag{2.11}$$

The CD test is distributed as a standard Normal when $N \rightarrow \infty$ and T is sufficiently large. Both tests do not account for the problem of proximity in the data. To deal with this, the weak cross-sectional dependence test developed by Pesaran (2004) accounts for an appropriate subset of neighboring cross-sectional units to check the null of no cross-sectional dependence against the alternative of local cross-sectional dependence. The test is called CD(s)

$$CD(s) = \sqrt{\frac{1}{\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \omega(\rho)_{ij}}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \omega(\rho)_{ij} \sqrt{T_{ij}} \hat{\rho}_{ij} \right), \tag{2.12}$$

where $\omega(\rho)_{ij}$ is the i,j-th element of the proximity matrix of order p-th with T_{ij} being the number of observations of the time series in common between individuals i and j. The CD(s) test overcomes the strict cross-sectional dependence problems of the basic CD test.

Unit-roots

A unit root is a statistical concept indicating that a time series variable has a stochastic trend and does not revert to a constant mean over time.

Usually, unit root tests in panel data are of two types. The first refers to the "first-generation unit root test", based on cross-sectional independence between units. The second type of test is the "second-generation unit root test", based on cross-sectional augmented statistics, depending on the CD test result.

This work uses the Cross-sectional dependence versions of the Augmented Dickey-Fuller (CADF) and Augmented Im, Pesaran, and Shin (CIPS) proposed by Pesaran (2007).[6]

The CADF statistic can be obtained from the regression given below

$$\Delta y_{it} = d_i + \phi_i y_{i,t-1} + c_i \bar{y}_{t-1} + \sum_{j=0}^{s} \beta_{ij} \Delta \bar{y}_{t-j} + \sum_{j=1}^{s} \gamma_{ij} \Delta \bar{y}_{i,t-j} + \varepsilon_{it}, \tag{2.13}$$

where d_i is the deterministic component, $\bar{y}$ and $\Delta\bar{y}$ are the cross-sectional averages of lagged levels and first differences, respectively, at time T for all countries. The t statistic of ϕ estimated from the equation (2.13) is then used to calculate the CIPS statistic, which can be represented as follows

$$\mathrm{CIPS} = \frac{1}{N} \sum_{i=1}^{N} \mathrm{CADF}_i \tag{2.14}$$

where CADF_i are the t-statistics of ϕ_i, estimated from Eq. (2.13). Both the CADF and CIPS tests are performed under the null hypothesis of homogeneous non-stationarity of the variables

$$H_0 : \phi_i = 0 \quad \forall i = 1, 2, \ldots, N \tag{2.15}$$

Cointegration

As well as the first-generation panel unit root tests, the most widely used panel cointegration estimators, such as Kao (1999) and Pedroni (2004), do not account for panel

[6] There are other unit root tests (augmented by cross-sectional units), such as Breitung and Das (2005) and Hadri (2000), but they assume, under the null hypothesis, that all panels have the same value of the autoregressive term (ϕ). The Im et al. (2003) test relaxes the assumption of a common ϕ, allowing each panel to have its own autoregressive coefficient.

cross-sectional dependence. Therefore, Westerlund (2007) developed four new panel cointegration tests based on structural rather than residual dynamics, thus not imposing any common factor restrictions. The idea is to test the null hypothesis of no cointegration by inferring whether the error correction term in a conditional panel Error Correction Model (ECM) is zero. When the data exhibit heterogeneity and cross-sectional dependence, these methods outperform the standard Pedroni (2004) and Kao (1999) methods.

Let the ECM generats from a DGP as follows

$$\Delta y_{it} = \delta_i' d_t + \sum_{j=1}^{P} \phi_{ij} \Delta y_{i,t-j} \sum_{p=1}^{Q} \beta_{ip} \Delta x_{i,t-p} - (1-\phi_i)[y_{it-1} - \beta_i x_{it-1}] + \varepsilon_{it}, \tag{2.16}$$

where t=1,...,T and i=1,...,N are the time-series and cross-sectional units. The term d_t contains the deterministic components, y is the endogenous variables vector and x comprehends the exogenous variables. The element $(1-\phi_i) = \lambda_i$, is the loading factor that determines the speed of adjustment after a sudden shock toward the long-run equilibria defined by the $y_{it} - \beta x_{it}$ relation. Therefore, we can state the null hypothesis of no cointegration as

$$H_0 : \lambda_i = 0, \quad \forall i = 1, 2, \ldots, N. \tag{2.17}$$

The alternative hypothesis depends on what is being assumed about the homogeneity of ϕ_i. Two of the tests, called group-mean tests, do not require the $\phi_{i,s}$ to be equal, which means

$$H_1 : \phi_i < 0 \text{ for at least one } i.$$

The second pair of tests, called panel tests, assume that ϕ_i is equal for all i and are, therefore, designed to test H_0 against

$$H_1 : \phi_i = \phi < 0, \forall i = 1, 2, \ldots, N.$$

Notably, the group statistic tests the existence of cointegration in at least one of the cross-sectional units. Quite the opposite, the panel statistic examines cointegration among all cross-sections within the panel. When cross-sectional dependence is present, the bootstrap approach reduces the bias. The test details are reported in Appendix 2.B.

Panel regression methodology

According to Eberhardt (2012), to account for slope heterogeneity and cross-sectional dependence the Common Correlated Effect Mean Group (CCEMG) estimator by Pesaran (2006) can be used. Basically, the idea is that, for relatively large N, a number of f_t factors can be approximated by the cross-sectional averages of regressors. Consider the model

$$y_{it} = \alpha_i + \beta_i' x_{it} + u_{it} \quad \text{with} \quad u_{it} = \delta_i' f_t + \varepsilon_{it}, \tag{2.18}$$

where α_i is the individual fixed-effects,[7] β_i are the heterogeneous coefficients randomly distributed around a common mean, $\beta_i = \beta + \nu_i, \nu_i \sim IID(0, \sigma_\nu)$, f_t is an unobserved common factor and δ_i is a heterogeneous factor loading. The regressors x_{it} are generated by linear combinations of the unobserved, cross-sectionally invariant factors f_t:

$$x_{it} = \omega_i + \lambda_i' f_t + v_{it}. \tag{2.19}$$

Putting together Equation (2.18) and (2.19), leads to the following setup

$$\underbrace{\begin{bmatrix} y_{it} \\ x_{it} \end{bmatrix}}_{\mathbf{z}_{it}} = \underbrace{\begin{bmatrix} 1 & \beta_i' \\ 0 & I_n \end{bmatrix} \begin{bmatrix} \alpha_i \\ \omega_i \end{bmatrix}}_{\mathbf{d}_t} + \underbrace{\begin{bmatrix} 1 & 0 \\ \beta_i & I_N \end{bmatrix} \begin{bmatrix} \delta_i \\ \lambda_i \end{bmatrix}}_{\mathbf{C}'_{it}} f_t + \underbrace{\begin{bmatrix} \varepsilon_{it} + \beta_i' u_{it} \\ v_{it} \end{bmatrix}}_{\mathbf{v}_{it}}. \tag{2.20}$$

From Equation (2.20) the cross-section averages can be defined as

$$\bar{\mathbf{z}}_{it} = \bar{\mathbf{d}}_t + \bar{\mathbf{C}}' f_t + \bar{\mathbf{v}}_{it}. \tag{2.21}$$

Then, if the sum of squares of $\bar{\mathbf{C}}$ is invertible, the common factors can be written as:

$$\mathbf{f} = (\bar{\mathbf{C}}'\bar{\mathbf{C}})^{-1}\bar{\mathbf{C}}(\bar{\mathbf{z}} - \bar{\mathbf{d}} - \bar{\mathbf{v}}). \tag{2.22}$$

[7] According to Pesaran (2006), a general deterministic time trends can be added.

If N $\to \infty$, then $\bar{\mathbf{v}} \xrightarrow{p} 0$ and $\bar{\mathbf{C}} \xrightarrow{p} \mathbf{C}$, the estimator is consistent since $\mathbf{f} - (\bar{\mathbf{C}}'\bar{\mathbf{C}})^{-1}\bar{\mathbf{C}}(\bar{\mathbf{z}} - \bar{\mathbf{d}} - \bar{\mathbf{v}}) \xrightarrow{p} 0$. Pesaran (2006) shows that the cross-sectional averages of the response ($\bar{y}_t$) and regressors ($\bar{x}_t$) are N-consistent estimators of the unobserved common factors and can therefore be used as observable proxies for them.

The usage of these averages takes the name of Augmenting regression with common correlated effect (CCE) which can be also an estimator for β by computing OLS to the augmented regression:

$$y_{it} = \alpha_i + \beta_i' x_{it} + \theta_i' \mathbf{w}_t + \varepsilon_{it} \quad \text{with} \quad \mathbf{w}_t = (\bar{y}_t, \bar{x}_t)'. \tag{2.23}$$

The vectors $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are estimated through a GLS transformation:

$$\gamma = \begin{bmatrix} \hat{\beta} \\ \hat{\theta} \end{bmatrix} = (x_{it}' \bar{M} x_{it})^{-1} x_{it}' \bar{M} y_{it} \quad \text{with} \quad \bar{M} = \mathbf{I} - \bar{H}(\bar{H}'\bar{H})^{-1}\bar{H}', \tag{2.24}$$

where $\mathbf{I}$ is the identity matrix, $\bar{H}$ is the $T(K+1)$ matrix of cross-sectional averages of $\mathbf{w}_t$ and the deterministic component comprising individual intercept and time trend. Now the average follow a Mean Group (MG) specification building the so called estimator of “Common Correlated Effects Mean Groups”:

$$\hat{\gamma}_{CCEMG} = \frac{1}{N}\iota'\hat{\gamma}. \tag{2.25}$$

The CCEMG estimator is consistent for any fixed, unknown number of possibly non-stationary common factors. Pesaran and Tosetti (2011) show that CCE estimator is robust from both strong and weak forms of cross-section dependence.[8]

However, this estimator is static, thus it does not allow for the consideration of lags in the dependent variable. To increase consistency, we account for the Autoregressive part employing the Dynamic Common Correlated Effect Mean Group (DCCEMG) by Chudik and Pesaran (2015). This estimator is consistent under stationary of variables. According to Chudik and Pesaran (2015) and Ditzen (2019), the DCCEMG reviews

[8] According to Chudik et al. (2011) and Kapetanios et al. (2011), the estimator was proved consistent under a variety of further assumptions on the error term.

Equation (2.23) including the lag of the dependent variable:

$$y_{it} = \alpha_i + \sum_{j=1}^{p_y} \phi_{ij} y_{i,t-j} + \sum_{k=0}^{p_x} \beta'_{ik} x_{i,t-k} + \sum_{m=0}^{p_{CS}} \delta_{im} \mathbf{w}_{t-m} + \varepsilon_{it}. \tag{2.26}$$

Chudik and Pesaran (2015) proposed to include $p_{CS} = \sqrt[3]{T}$ lags of the cross-sectional averages to reduce the bias and to gain consistency. Then, according to Chudik et al. (2016) and Ditzen (2021) the short-run coefficients are obtained and used to compute the long-run coefficients

$$\hat{\gamma}_{LR-ARDL,i} = \frac{\sum_{k=1}^{p_x} \hat{\beta}_{ik}}{1 - \sum_{j=1}^{p_y} \hat{\phi}_{ij}} \tag{2.27}$$

where $\hat{\beta}$ and $\hat{\phi}$ are the short-run estimations of parameters. The individual long-run covariance matrix is estimated via Delta Method (see, Ditzen (2019) for details). Among others, this specification is partially followed in Khan et al. (2020), Ma et al. (2021), Khan et al. (2021b), Noureen et al. (2022) and Chien et al. (2022).

Heterogeneous panel causality analysis

In standard time series analysis, causality between series is determined by the so-called Granger Causality (GC) procedure, which goes through the estimation of a VAR(p) model. In many empirical studies GC is used extensively, sometimes inappropriately. Generalization in a panel framework has been employed by Dumitrescu and Hurlin (2012) - named DH. Let us consider the standard panel regression:

$$y_{it} = \alpha_i + \sum_{k=1}^{K} \sum_{s=1}^{P} \phi_{iks} y_{ikt-s} + \sum_{k=1}^{K} \sum_{l=1}^{Q} \beta_{ikl} x_{ikt-l} + \varepsilon_{it}, \tag{2.28}$$

where y and x are stationary time-series and the lags of the variables are determined by the lowest IC. The coefficients may differ between individuals, but they are assumed to be invariant over time. As in Granger (1969), the procedure for determining the existence of causality is to test the significant effects of past values of x on the present value of y. The null hypothesis will be:

$$H_0 : \beta_{i1} = \beta_{i2} = \cdots = \beta_{ik} = 0, \tag{2.29}$$

which corresponds to the absence of causality for all individuals in the panel. The DH test assumes there can be causality for some individuals but not necessarily for all.

The first proposed step in the DH procedure involves running the N individual regressions in the original panel set specified in the equation (2.28), running the F-test of βs significance defined in the equation (2.29), and specifying the Wald (W) statistic. Using Monte Carlo simulations, Dumitrescu and Hurlin (2012) show that $\bar{W}$ behaves asymptotically well and can really be used to investigate panel causality.

Wald's W_i statistic under the null hypothesis is the absence of causality for all panels of individuals, considering an iid distribution among individuals, when properly standardized (Z) follows a normal distribution:

$$\bar{Z} = \sqrt{\frac{N}{2K}}(\bar{W} - K) \xrightarrow{d} N(0,1) \tag{2.30}$$

This statistic holds when T $\rightarrow \infty$ faster than N. For a fixed T dimension with $T > 5 + 3K$, the approximated standardized statistic $\tilde{Z}$ follows a standard normal distribution

$$\tilde{Z} = \sqrt{\frac{N}{2K}\frac{T-3K-5}{T-2K-3}}\left(\frac{T-3K-3}{T-3K-1}\right)(\bar{W} - K) \xrightarrow{d} N(0,1). \tag{2.31}$$

The verification procedure is based on the two normalized calculated statistics, $\tilde{Z}$ and $\bar{Z}$. When these values are greater than the critical values, H_0 should be rejected and the conclusion leads to the existence of Granger causality. For panels of N and T of large size, one can reasonably consider $\bar{Z}$. For data sets with large N but relatively small T, one should favor $\tilde{Z}$. The empirical problem of cross-dependence can be addressed by the bootstrap technique:

Step 1: Fit the original Equation (2.28) to obtain $\bar{Z}$ and $\tilde{Z}$, as defined in (2.30) and (2.31);

Step 2: Fit the model under H_0:

$$y_{it} = \alpha_i + \sum_{k=1}^{K}\sum_{s=1}^{P}\phi_{ik}y_{ikt-s} + \nu_{it},$$

and save the estimated residuals ($\hat{\nu_{it}}$). More in details, the residuals obtained from the equation must be collected in a matrix of dimension `(T-K)`$\times$`N`;

Step 3: Build a matrix ν_{it}^* of dimension `(T-K)`$\times$`N` by resampling (overlapping blocks of) rows (that is, time periods) of matrix $\hat{\nu_{it}}$. If autocorrelation is present (block) bootstrap can mitigate the issue.

Step 4: Generate a random draw $\mathbf{y}_1^*, \mathbf{y}_2^*, \ldots, \mathbf{y}_n^*$, with $\mathbf{y}_1^* = y_{1t}^*, y_{2t}^*, \ldots, y_{Nt}^*$, from the model under H_0 and the residuals $\hat{\nu_{it}}$, by randomly selecting a block of K consecutive time periods with replacement (see Stine (1987) and Berkowitz and Kilian (2000)).

Step 5: Generate the timeseries under H_0:

$$y_{it}^* = \hat{\alpha}_i^0 + \sum_{k=1}^{K} \sum_{s=1}^{P} \hat{\phi}_{ik}^0 y_{ikt-s}^* + \nu_{it}^*,$$

conditional on the random draw for the first K periods.

Step 6: Fit the model in Equation (2.28) with the random draw:

$$y_{it}^* = \alpha_i^b + \sum_{k=1}^{K} \sum_{s=1}^{P} \phi_{ik}^b y_{ikt-s}^* + \sum_{k=1}^{K} \sum_{l=1}^{Q} \beta_{ik} x_{ikt-l} + \varepsilon_{it},$$

and compute $\bar{Z}^b$ and $\tilde{Z}^b$.

Boot: Run the resampling procedure (Step 1 to 6) B times and compute the p-values and critical values for $\bar{Z}$ and $\tilde{Z}$ based on the distributions of $\bar{Z}^b$ and $\tilde{Z}^b$, where b is the number of bootstrapped resampling.

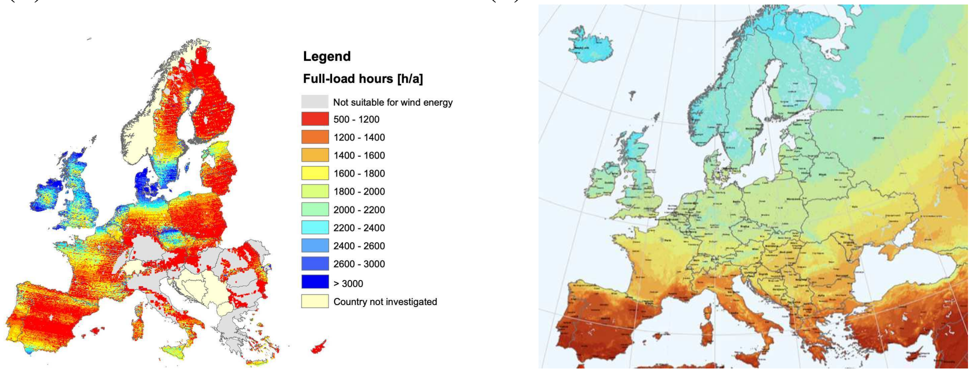
2.3.2 Data

Based on data availability, we consider yearly data from 1990 to 2022 ($T = 33$) for a total panel of $N = 33$ countries that refer to the European geographical area.[9] In our case, we consider the geographical division essential as energy consumption,

[9] Austria, Belgium, Belarus, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom (UK).

especially renewable energy sources, depends on the geographical characteristics of the territories. For example, solar (wind) energy availability in southern (northern) countries is higher than in the northern (southern) nations (Figure 2.3).

(A) Wind Availability in the EU (B) Solar Electricity Potential in EU



Source: Held (2010) Source: Talebi et al. (2016)

Figure 2.3: Comparison of Solar and Wind availability in the EU

The primary objective of this study is to investigate the CO2 determinants, while simultaneously studying the mutual relationship between renewable energy consumption, environmental degradation, and economic growth. Given the discussion in Luzzati et al. (2018), it is evident how the model specification, the sample, and the used variables influence the validity of estimations. For this reason, we restrict the sample to European countries and we follow the literature to include several controls to mitigate the omitted variable bias.

Our main variables of interest are the Renewable Energy Consumption (REC) measured in terawatt-hours and the carbon dioxide emissions (CO2) measured in million tonnes as a proxy of environmental degradation. We employ the GDP corrected per capita instead of GDP at chained prices because it provides a more accurate indicator for capturing the economic welfare of countries, while simultaneously accounting for potential inflationary effects. We include a square term of the GDP to account for the non-linear relationship between environmental degradation and economic growth.

According to Apergis and Tang (2013), as discussed in Section 2.2, the study acknowledges the importance of including three or more relevant control variables in the estimation to address the omitted variable problem. As a result, we incorporate the total Primary Energy Consumption (PEC), measured in terawatt-hours, the PEC

Main variables	
GDP	Per capita Gross Domestic Product https://data.worldbank.org/indicator/NY.GDP.MKTP.KD
REC	Renewable Energy Consumption https://ourworldindata.org/renewable-energy
CO_2	Environmental degradation https://ourworldindata.org/co2-and-greenhouse-gas-emissions
Control variables	
PEC	Primary energy consumption https://ourworldindata.org/energy
COAL	Coal energy consumption https://ourworldindata.org/energy
URB	Urban population https://data.worldbank.org/indicator/SP.URB.TOTL
LF	Labor force https://data.worldbank.org/indicator/SL.TLF.TOTL.IN

Table 2.3: Variables with URL

from coal, measured in terawatt-hours (COAL), urban population (URB), and the total amount of labor force (LF).[10] These selected control variables have been selected according to Section 2.2.3 since they play a crucial role in this context to reduce the endogeneity issue (see Table 2.3 for source details). In Appendix 2.C, we report a panel-by-panel graphical representation of the main variables and Table 2.4 reports the descriptive statistics.

	CO2	GDP	REC	URB	LF	COAL	PEC
mean	133.8906	28870.64	73.0752	1.20e+07	8.8095	121.9402	693.6288
sd	187.9506	22953.05	110.4397	1.54e+07	12.0187	217.0605	916.2582
min	2.104	1317.746	0	231255	0.1428	0	19.275
max	1054.741	112417.9	727.48	6.53e+07	56.5225	1529.691	4192.642

Table 2.4: Summary Statistics

First, we estimate the following dynamic heterogeneous panel data model

$$\ln CO2_{it} = \alpha_i + \sum_{j=1}^{p_y} \phi_{ij} \ln CO2_{it-j} + \sum_{k=0}^{p_x} \beta'_{lik} Z_{it-k} + \sum_{m=1}^{p_{CS}} \delta_{im} \mathbf{w}_{t-m} + \varepsilon_{it} \tag{2.32}$$

where Z is the vector of explanatory variables expressed in logarithmic terms

$$Z'_{it} = (REC_{it}, GDP_{it}, GDP^2_{it}, LF_{it}, COAL_{it}, PEC_{it}, URB_{it})', \tag{2.33}$$

[10] Alternatively, we could have used the number of hours worked or labor productivity, but in some cases we had several missing values and we proceed by considering the total amount of workforce.

and **w** represents the averages for cross sections. We consider log to compute elasticities.

The general representation expressed in Equation (2.32) leads to the computation of the long-run coefficients as discussed in Equation (2.27). The idea is that the long-run relationship can be considered as a sort of market equilibria. The short-run coefficients represent the fluctuations around the long-run relationship. The inclusion of the squared GDP term allows to test the include any non linearities in the CO2-GDP relationship. The average non linear relationship between economic growth and carbon dioxide emissions seems to emerge from Figure 2.4.

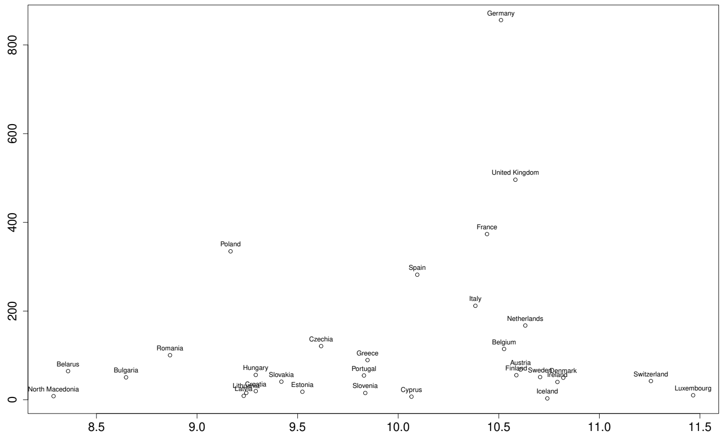


Figure 2.4: Scatterplot of average log per capita GDP (x-axis) and CO2 (y-axis)

We revise Equation (2.32), including different renewable energy sources. In particular, we innovate the literature considering four different categories of REC: hydroelectric (HY), nuclear (NC), solar (SC), and wind (WC) consumption. In particular, we consider 2 additional model specifications one with RES and the other with nuclear energy, to distinguish for renewable and clear energy effects. A noteworthy consideration is that some countries may report zero values for specific renewable energy types (see Appendix 2.D for a graphical representation). This is due to factors such as the limited availability or adoption of specific renewable technologies. Accordingly, these variables are not log-transformed, allowing the coefficients to be interpretable as semi-elasticities.

Since the literature has not investigated the role of economic growth on renewable energy consumption of this type of heterogeneous panels after the Paris Agreement (2015), we apply the DCCEMG model in estimating the following linear panel data equation

$$\ln REC_{it} = \alpha_i + \sum_{j=1}^{p_y} \phi_{ij} \ln REC_{it-j} + \sum_{k=0}^{p_x} \beta'_{lik} Q_{it-k} + \sum_{m=1}^{p_{CS}} \delta_{im} \mathbf{w}_{t-m} + \varepsilon_{it} \quad (2.34)$$

where REC is expressed in logs, Z is the vector of explanatory variables (in logs)

$$Q'_{it} = (CO2_{it}, GDP_{it}, GDP^2_{it}, LF_{it}, COAL_{it}, PEC_{it}, URB_{it})', \quad (2.35)$$

and **w** represents the averages for individuals.

Finally, to understand the role of energy consumption on economic growth, we estimate the model with the GDP as the dependent variable while REC and CO2 are included in the set of regressors

$$\ln GDP_{it} = \alpha_i + \sum_{j=1}^{p_y} \phi_{ij} \ln GDP_{it-j} + \sum_{k=0}^{p_x} \beta'_{lik} T_{it-k} + \sum_{m=1}^{p_{CS}} \delta_{im} \mathbf{w}_{t-m} + \varepsilon_{it} \quad (2.36)$$

where GDP per capita is expressed in log and Z is the vector of explanatory variables (in logs)

$$D'_{it} = (CO2_{it}, REC_{it}, LF_{it}, COAL_{it}, PEC_{it}, URB_{it})', \quad (2.37)$$

and **w** represents the averages for cross-sections. Also in this case the renewables are broken down individually.

Since we deal with yearly data, we set the autoregressive order equals to one ($p_y = 1$), such as the lag in the exogenous variables ($p_x = 1$). Since $T = 33$, we follow Chudik and Pesaran (2015) setting $p_{CS} = 3$. As a result, we estimate in each case a CS-ARDL(1,1,3).[11]

[11] We tested the model of the equation (2.36) considering any non-linearities in CO2 emissions and REC, including their squared terms in the set of regressors expressed in the vector D_{it} in Eq. (2.37), but we find no statistical evidence. To not make the tables burden, we do not include this case but it is available upon request.

2.4 Results and policy implications

Preliminary diagnostic statistics are given in Table 2.5 and 2.6. The heterogeneity tests (Δ and Δ_{HAC}), reveal how the null hypothesis of the homogeneous slope coefficients is strictly rejected. In addition, the rejection of the no-cross-sectional dependence in the CD test underscores the need for an estimator that can address both problems.

Long panels are characterized by extended time series data, typically with T values exceeding 25, commonly dealing with macroeconomic time series. In such datasets, issues related to non-stationarity and cointegration often arise. To assess the presence of unit roots and cointegration in our data, we conducted second-generation unit root tests using the Unit Root (CADF, CIPS) and cointegration tests (Westerlund). These tests were conducted with both constant and trend components in the deterministic part, indicating the existence of unit roots and cointegration. When examining the bootstrapped pvalues, all tests considering different alternative hypothesis reject the null hypothesis of no cointegration. Therefore, the DCCEMG estimator is the most suitable in our case. It is worth noting that some studies still employ fully modified or dynamic OLS despite their comparatively poorer performance in statistical inference.

	CDw	CDw+	CADF	CIPS
CO2	-1.07	1521.68***	19.2597	4.8007
REC	2.64***	2095.05***	59.0895	2.4973
GDP	4.68***	2407.08***	30.2985	3.4239
COAL	-3.34***	1618.97***	76.7054	0.1668
URB	-2.98***	2360.61***	65.7840	3.5431
LF	2.14***	2209.13***	94.9104***	0.8254***
PEC	10.34***	1253.98***	220.5682***	-6.5679***

$^{*}5\% < p < 10\%,^{**} 1\% < p < 5\%,^{***} p < 1\%$

Note: The Slope Heterogeneity test Δ = 22.608***, Adjusted Δ_{HAC} = 25.973***

Table 2.5: Diagnostic tests

DCCEMG Results

First, we study the CO2 determinant, then, we explore the dynamic relationship between economic growth and energy consumption. Finally, we apply the test proposed

Statistic	Value	Z-value	P-value	Robust P-value
G_t	-2.782	-3.296	0.001	0.000
G_a	-13.266	-1.849	0.032	0.000
P_t	-14.577	-3.513	0.000	0.040
P_a	-9.771	-1.994	0.023	0.050
VR_{single}	-2.2032		0.03	
VR_{total}	5.61		0.00	

Note: the robust p-value is obtained through 100 bootsrap iteration. The VR test is the Westerlund (2005) test.

Table 2.6: Panel Cointegration tests

by Dumitrescu and Hurlin (2012) to identify causality between these variables and ensure the robustness of our findings.[12] Table 2.7 reports the estimations of Equations 2.32, 2.34, and 2.36.

2.4.1 The non linear effect of GDP on CO2

Since the lagged value of CO2 is not significant, we need to study the dependence of CO2 on external variables, such as economic development and energy consumption. Given the longer-term perspective of the relationship between environmental degradation and economic growth, Equation (2.32) focuses on the long-run outcomes (Table 2.7, first column).

We found an inverted U-shape relationship between CO2 and per capita GDP with a turning point estimated at \$34822.53, which surpasses the average GDP of the sample (\$28870.64). We can study the different decoupling stages of European countries, thereby enhancing the implications associated with the worsening environmental conditions. In our context, the decoupling stage (refer to Mikayilov et al., 2018, and Figure 2.14) involves substituting the average GDP value (or country-specific values) within the panel and comparing its value relative to the turning point, examining the sign of the derivative.

Since the turning point is higher than the average GDP per capita of the sample, European countries are (on average) in the early stages of industrialization and on the path of relative decoupling, confirming the conclusions discussed in Mikayilov et al. (2018) and Gyamfi et al. (2021). Table 2.8 shows the list of countries before and after

[12] We decided not to include country-by-country estimates to allow for a more readable result and conclude about global average policies. In some cases, we report the country-by-country estimates in bar plots.

Dep.Var	Equation (2.32)			Equation (2.34)					Equation (2.36)		
	$\ln CO2$			$\ln REC$	HY	NC	SC	WC	$\ln GDP$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Short-Run											
$\ln CO2_t$				-1.944**	-102.9**	-64.41	3.633	-48.10	0.399**	-2.228	0.280**
				(0.381)	(34.59)	(51.43)	(12.77)	(34.00)	(0.142)	(2.872)	(0.109)
$\ln CO2_{t-1}$	-0.0266	0.0300	-0.103	0.5754	-77.26	-56.82*	21.73	47.91	-0.00519	2.140	0.0381
	(0.0611)	(0.0715)	(0.0748)	(0.520)	(72.08)	(30.37)	(29.98)	(34.69)	(0.0607)	(2.268)	(0.107)
$\ln REC_t$	-0.0977***								0.0166		
	(0.0283)								(0.0191)		
$\ln REC_{t-1}$	0.00336			0.2369**					-0.0200*		
	(0.0220)			(0.12)					(0.01)		
$\ln GDP_t$	-1.447	9.491*	2.764	28.3213	4102.2*	-4974.8	-963.8*	-753.9			
	(4.736)	(5.120)	(7.344)	(27.36)	(2254.5)	(3149.7)	(552.9)	(602.3)			
$\ln GDP_{t-1}$	7.556	5.971	-3.530	6.9301	-1639.4	12337.1	-2589.3	-3798.6	0.394***	1.020	0.256**
	(5.151)	(9.427)	(6.944)	(43.029)	(5559.5)	(9373.7)	(2011.4)	(2632.0)	(0.0776)	(1.162)	(0.0898)
$\ln^2 GDP_t$	0.0598	-0.440*	-0.123	-1.440	-196.6*	236.0	45.94*	35.18			
	(0.228)	(0.246)	(0.349)	(1.37)	(108.2)	(150.2)	(26.33)	(29.35)			
$\ln^2 GDP_{t-1}$	-0.378	-0.275	0.156	-0.2493	72.63	-591.7	124.5	183.7			
	(0.239)	(0.443)	(0.329)	(2.10)	(266.5)	(443.6)	(97.73)	(125.6)			
HY_t		-0.0306								-0.0360	
		(0.0290)								(0.120)	
HY_{t-1}		-0.00857			-0.250***					0.395	
		(0.0330)			(0.0718)					(0.369)	
NC_t			-0.001								-0.0006*
			(0.0007)								(0.0003)
NC_{t-1}			-0.0006			-0.101*					-0.0006
			(0.0005)			(0.0557)					(0.0009)
SC_t		0.216								-0.237	
		(0.378)								(0.493)	
SC_{t-1}		-0.789					0.721***			0.106	
		(0.507)					(0.158)			(0.555)	
WC_t		-0.175**								-2.714	
		(0.088)								(2.308)	
WC_{t-1}		0.179						-0.00138		-0.641	
		(0.194)						(0.102)		(0.550)	
Long-Run											
$\ln CO2$				1.121***	2.580	0.322	1.759	0.343	-0.606***	-1.088	-0.682***
				(0.525)	(1.646)	(0.214)	(1.577)	(0.290)	(0.171)	(3.973)	(0.180)
$\ln GDP$	10.27**	20.52**	-1.130	29.2558	-17.57	-4.280	-6.336	6.874			
	(4.857)	(8.077)	(6.490)	(26.7587)	(67.08)	(18.51)	(39.29)	(29.29)			
$\ln^2 GDP$	-0.538**	-0.965**	0.0463	-1.3905	1.270	0.167	0.204	-0.251			
	(0.252)	(0.388)	(0.315)	(1.25)	(3.531)	(0.881)	(1.929)	(1.388)			
$\ln REC$	-0.156**								-0.0957*		
	(0.0606)								(0.0579)		
HY		0.0941								-0.0531	
		(0.189)								(0.104)	
SC		-0.511**								-0.815	
		(0.240)								(1.226)	
WC		0.00669								0.347	
		(0.147)								(0.396)	
NC			-0.003**								0.0004
			(0.0014)								(0.005)

Note: Dynamic CCEMG estimation with control variables (PEC, LF, URB, COAL) included but omitted in the representation for space reasons. Full estimations with control variables are available upon request.

Table 2.7: Panel data estimation

the estimated turning point. In fact, the heterogeneity of the panel emerges because the countries of Eastern Europe are the majority in the industrialization phase, while those of the South are in the transitional phase and those of the North are in a more advanced phase.

Before turning point	After Turning point
Belarus, Bulgaria, Croatia, Cyprus, Czechia, Estonia, Greece, Hungary, Latvia, Lithuania, North Macedonia, Poland, Portugal, Romania, Slovakia, Slovenia, Ukraine	Austria, Belgium, Denmark, Finland, France, Germany, Iceland, Ireland, Italy, Luxemburg, Netherlands, Norway, Spain, Sweden, Switerland, UK

Table 2.8: Pre-Post Countries turning point

The most industrialized countries, such as those in Northern Europe, are in the absolute decoupling stage since their GDP is higher than the average where increased economic growth reduces environmental degradation, confirming the results of McKibbin et al. (2014) and Schandl et al. (2016). This result is also related to the high degree of renewable energy use and the downward trajectory of carbon dioxide emissions (see Figure 2.15). Additionally, in line with the findings of Mikayilov et al. (2018), European countries have actively pursued more stringent carbon mitigation policies (Paris Agreement, 2015) compared to other major economies such as China, the United States, and Russia.

Given the discussion in Wu et al. (2023), our results reinforce the importance of Nordic countries. Their increasing GDP and recent adoption of environmental policies aimed at expediting the transition to more sustainable energies underscore their growing relevance in lowering emissions. These findings align with Papież et al. (2021), who extensively discussed the efficacy of European environmental policies, especially for the wealthier countries, in promoting the decoupling process. A detailed discussion is presented in Section 2.4.3.

In terms of model specification we also tested the validity of the N-shaped relationship by considering a cubic GDP term, but no statistical evidence emerged.[13]

[13] Results are available upon request.

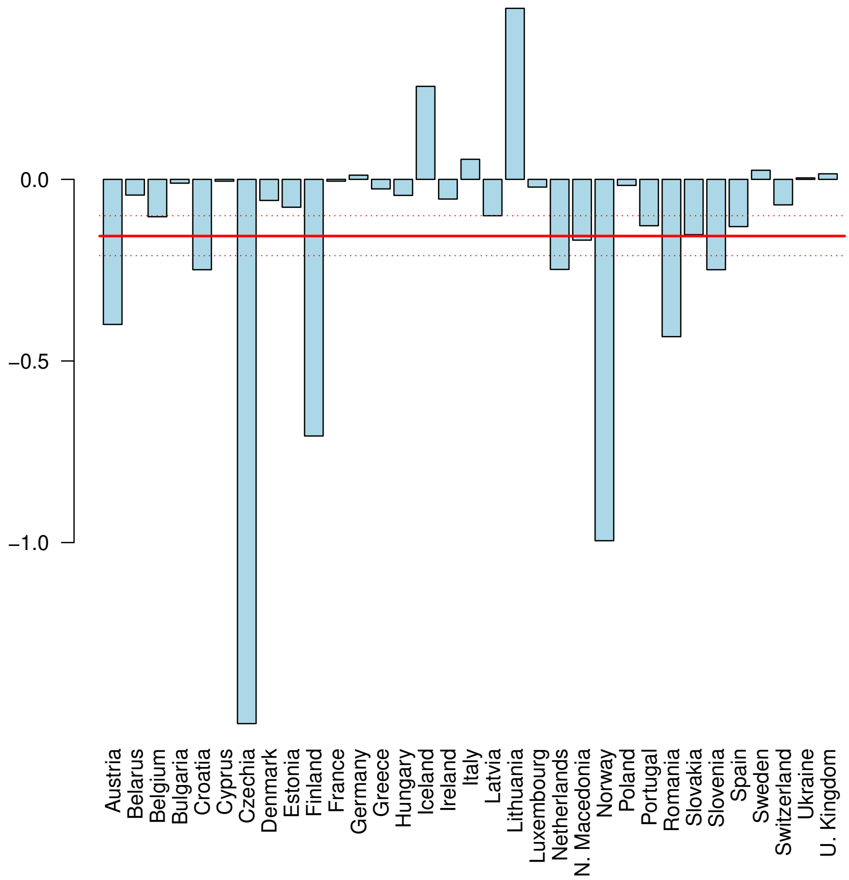
2.4.2 REC and environmental degradation

Equation (2.32) explores the association between REC and CO2. Since we have defined the logarithmic transformation, coefficients are interpretable as elasticities ($\varepsilon_{CO2,REC}$). On average, the short-term effect of the REC significantly reduces the amount of CO2 in the atmosphere with $\varepsilon_{CO2,REC}^{Short-run} = -0.0965$, confirming the role of the REC in reducing environmental pollution. This result strengthens in the long run with an elasticity of $\varepsilon_{CO2,REC}^{Long-run} = -0.156$. While from a worldwide perspective, REC usage is still marginal, European governments could gain from promoting REC via subsidies and incentives. This findings are in line with most of the literature (see, among others, Hu et al., 2018; Adams and Acheampong, 2019) but do not confirm Murshed et al. (2022).

However, given the high delocalization level of European companies, the pollution burden could be transferred to developing countries, thus producing negative externalities in promoting environmental improvement in Europe. Furthermore, it is essential to consider that consumer goods are produced in the rest of the world, particularly in Asian countries.

Figure 2.5 shows individual long-term $\varepsilon_{CO2,REC}$ estimates for each country. Given the average estimation result, in almost all cross-sectional units, a negative effect of the REC on CO2 emerged, with the exception of the Lithuanian case where the sign of $\varepsilon_{CO2,REC}^{Long-run}$ is positive and significant at 5%. Lithuania has reduced emissions more slowly than the EU average, as reported by Jensen and Seppala (2021). EU effort-sharing legislation has allowed Lithuania to increase its emissions by 15% (2020) to improve the country's economic development by promoting industrialization (IEA, 2021). This policy, combined with a relatively slower increase in the percentage of renewable energy use (see Figure 2.6), implies that the increase in REC is not useful for addressing the increase in environmental pollution at this stage, as evidenced by the increasing trajectory of greenhouse gases reported in Figure 2.6 since 2015.

From Figure 2.5 we could also find the $\varepsilon_{CO2,REC}^{Long-run}$ positive coefficient in the Iceland case. However, the coefficient is not significant, such as in Northern European countries (Denmark, Finland, Germany, Netherlands, Norway, and Sweden). On average, according to Wolf et al. (2022), the Environmental Performance Index places

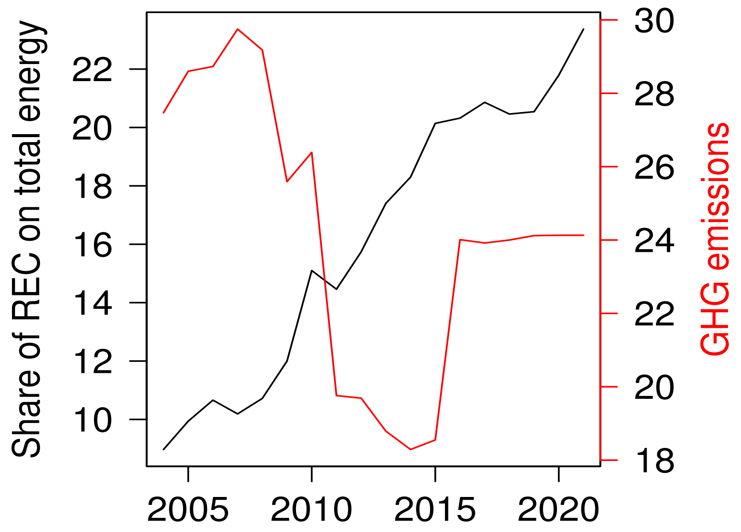


Note: The continous red line is the average coefficient reported in Table 2.7 column 1 while the dotted red lines are the confidence bands for the average coefficient.

Figure 2.5: Country-by-country estimation of $\varepsilon_{CO2,REC}^{Long-run}$, Eq. (2.32).

Iceland in 10th place, mostly behind the Nordic lands. This outcome implies that the environmental conditions in these countries significantly surpass those in the rest of the panel. Furthermore, it suggests that renewable energy consumption is not a determinant factor contributing to environmental degradation (see, for instance, Nathaniel et al., 2021). However, in other cases, especially in Eastern countries, the REC significantly reduces CO2.

Examining the results for each renewable energy source (col. 2 of Table 2.7), enlarge the implications of the work. We find a substantial impact of wind and solar energy in mitigating environmental degradation, particularly in the short and long term. This result is in line with Maka and Alabid (2022), who found that solar energy efficiently reduces environmental degradation. Furthermore, given the constant decrease in costs related to solar energy such as installation and maintenance (see the IRENA, 2022, report and Figure 1.3, Chapter 1), the energy policy formulation could



Source: https://ourworldindata.org/energy/country/lithuania

Figure 2.6: Lithuaninan REC on total energy and GHG emissions (measured in million tonnes of CO2-equivalents).

promote technologies aimed at containing solar energy costs and simultaneously improve climate conditions.

The long-term importance indicates that solar energy requires structural investments to produce environmental benefits, especially in Southern European countries where solar sources are significantly more available (see Figure 2.3). To strengthen this discussion, we report in Figure 2.7 panel (a) the role of the effect of solar energy consumption for each of the countries considered. The highest impact of SC on CO2 is found in southern (and eastern) European countries such as Italy and Spain.

As we saw from Figure 2.3, the availability of wind power plants in Northern Europe is further confirmed by the short-term effectiveness of wind in reducing carbon emissions. The immediate impact underscores the well-established influence of wind energy within the panel, particularly evident in the Nordic European countries and the noteworthy exception of Spain (refer to Figure 2.2). In this context, the studies conducted by de Castro et al. (2019) and Susini et al. (2022) delve into the potential enhancement of wind energy by proposing the establishment of plants in the North Sea, where winds are notably stronger.

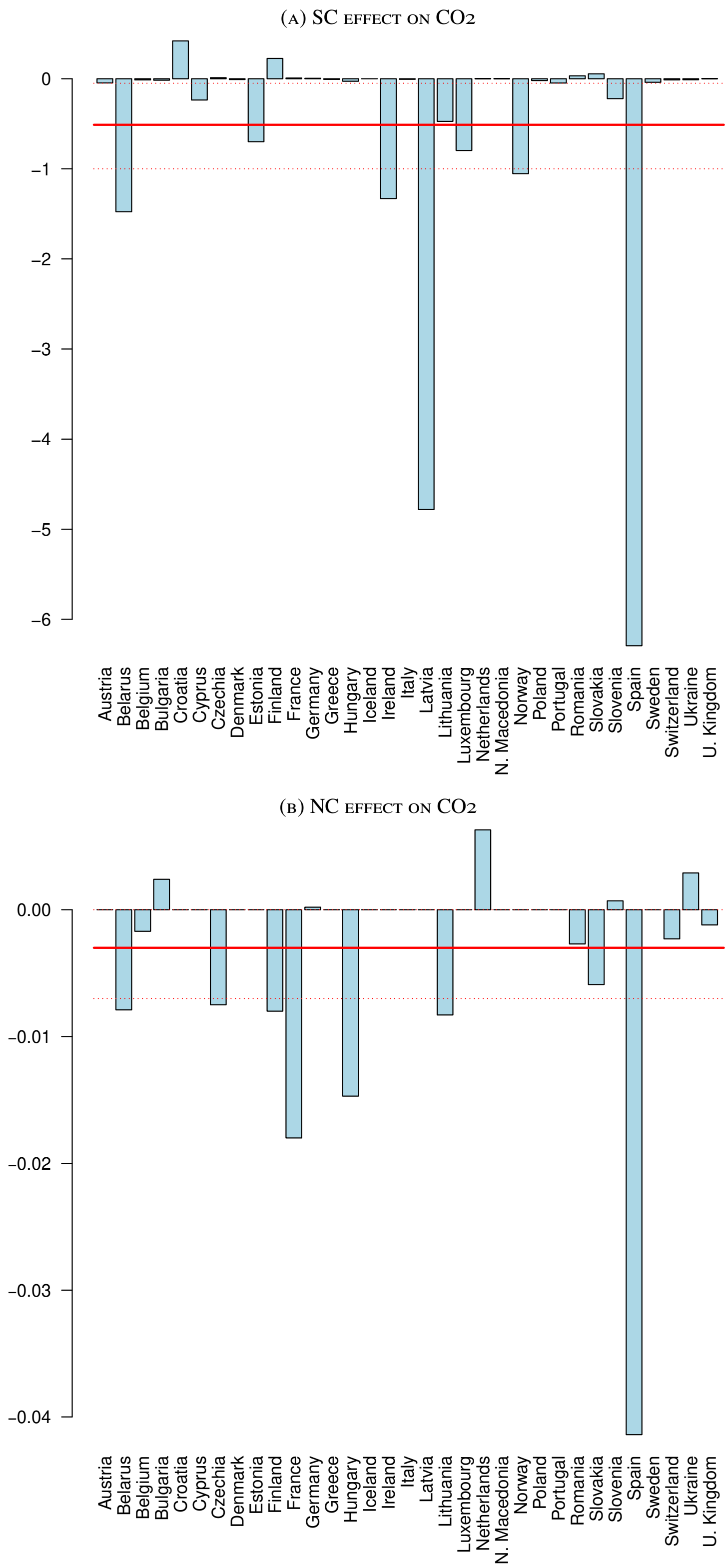
Column 3 of Table 2.7 shows the CS-ARDL estimates considering nuclear energy consumption (NC). The semi-long-run elasticity of the NC on CO2 is negative and significant, thus underlining the role of NC in improving environmental conditions. However, we need to consider the fact that several countries do not use nuclear energy as power plants, so in most cases the impact is zero. This result is in line with that of Nathaniel et al. (2021), Murshed et al. (2022), and Pan et al. (2023), who discovered a curbing role of nuclear energy on carbon dioxide emissions. In particular, we found a relevant role of France and Spain, see Figure 2.7.

Our findings highlight the importance of implementing long-term policies for solar and nuclear energy, which are significant drivers of environmental improvement in the long term. Investments in renewable plants could diversify the energy mix of families, making the impact of exogenous shocks on the energy market less pronounced. New renewable energy plants bring substantial environmental benefits to the real market. In particular, it has the potential to trigger various positive spillovers in other sectors, including job creation and strengthening geopolitical relations between countries.[14] Furthermore, developing cleaner energy alternatives can also produce higher financial returns, as demonstrated in studies such as Prokopenko et al. (2023).

On the contrary, looking at the result of Table 2.7 column 4, CO2 reduces the consumption of renewable energy in the short term, while it has a positive effect in the long term, especially when considering the total REC. This result is relevant because it underlines the role of social awareness in the long term and strengthens the effectiveness of growing regulations on limiting pollution while stimulating renewable energy sources.

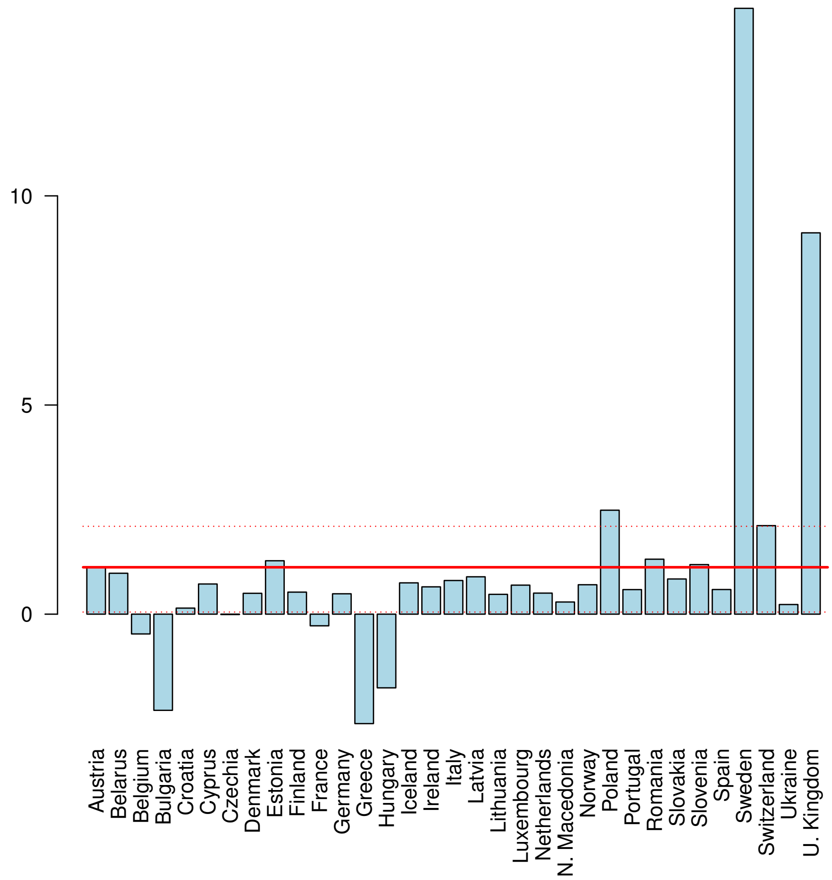
As reported in Figure 2.8, the maximum long-term positive impact of CO2 on REC is achieved in Sweden and the United Kingdom, where the estimated cross-sectional coefficient is above the average. In contrast, there are three countries where the impact of CO2 on the REC is negative and significant: Bulgaria, Greece, and Hungary. The main reason for this result is that these countries are relatively poorer than the sample average and rely more on traditional fossil fuels, which could increase their wealth. Therefore, while renewable energy consumption has increased, but relatively less than in other countries, they may continue to use these fossil factors, negatively affecting REC.

[14] For further discussion, please refer to Sen and Ganguly (2017) and Arcelay et al. (2021).



Note: The continous red line is the average coefficient reported in Table 2.7 columns 2-3, while the dotted red lines are the confidence bands for the average coefficient.

Figure 2.7: Country-by-country estimation of long-run renewable sources impact on CO2 (semi-elasticities), Eq. (2.32).



Note: The continous red line is the average coefficient reported in Table 2.7 column 4 while the dotted red lines are the confidence bands for the average coefficient.

Figure 2.8: Country-by-country estimation of $\varepsilon^{Long-run}_{REC,CO2}$ coefficients in Eq. (2.34)

Several interesting paths emerge in the short term when considering REC sources (columns 4 - 8). Although income is not relevant to total REC, we found a U-shaped relationship between income and solar energy (low point at GDP = \$35945.89), while an inverted U-shape emerged in the hydroelectric consumption case (highest point at GDP = \$33957.33). In the first case, it is a sign of how solar energy is used by wealthier countries, given its higher average cost compared to wind power. Quite the opposite, for higher income countries, the hydroelectric source is substituted by other renewable (such as solar). This result strengthens the discussion on the promotion of solar energy incentives.

2.4.3 REC and economic growth

Given the 10% significant value of $\varepsilon_{GDP,REC}$, the effect of renewable energy on economic growth is, on average, negative. This result is in line with Tsagkari et al. (2021) and Muazu et al. (2023), which report a detrimental role of renewable energy usage on economic growth. However, the outcome does not coexist with Alper and Oguz (2016a) and Kasperowicz et al. (2020), which determine the positive influence of renewable energy consumption.

Roughly this finding aligns with the "sustainable degrowth" (or decrease) theory, recently discussed in Van den Bergh (2011), Lorek and Fuchs (2013) and Sekulova et al. (2013).[15] According to Van den Bergh (2011), the role of social companies is crucial to guarantee an increase in a sustainable degrowth context. Moreover, this switch implies several simultaneous institutional changes, starting with the change of the corporate structure as a form of productive organization. Moreover, following the view expressed in Lorek and Fuchs (2013), the major problem in degrowth lies in the weak sustainable vision of economic agents. In particular, following the principles expressed by the theory of sustainable degrowth, corporate policy, and governance should lead to the production of better-quality products that are sufficient to address current ecological and social challenges.

Given the results of Sekulova et al. (2013), it will be necessary to disentangle the effect of renewable energy on GDP since this consideration cannot be extended to a group of different countries. To this end, we report in Figure 2.9 the country-by-country coefficients of $\varepsilon^{Long-run}_{REC,GDP}$. While almost all coefficients are negative, Iceland, Finland, and Switzerland have a positive coefficient, confirming Furuoka (2017).

Looking at Table 2.8 (or the preliminary scatterplot in Figure 2.4), Iceland, Finland, and Switzerland are in the absolute decoupling phase, as confirmed by the validity of the nonlinear relationship between CO2 and GDP. Therefore, given the well-structured integration of renewable energy in these countries, the consumption of renewable energy has a positive effect on economic growth. In the opposite case, the highest (negative) values are reached in Bulgaria, Greece, and Romania, which are on the upward path of the inverse U-shape relationship between CO2 and GDP. This

[15] This concept was broadly introduced by Daly (1973) and Georgescu-Roegen (1975).

result could raise the question of improving economic growth and renewable energy consumption while simultaneously containing CO2. In this sense, environmental economic policies are tough to implement without influencing economic growth.

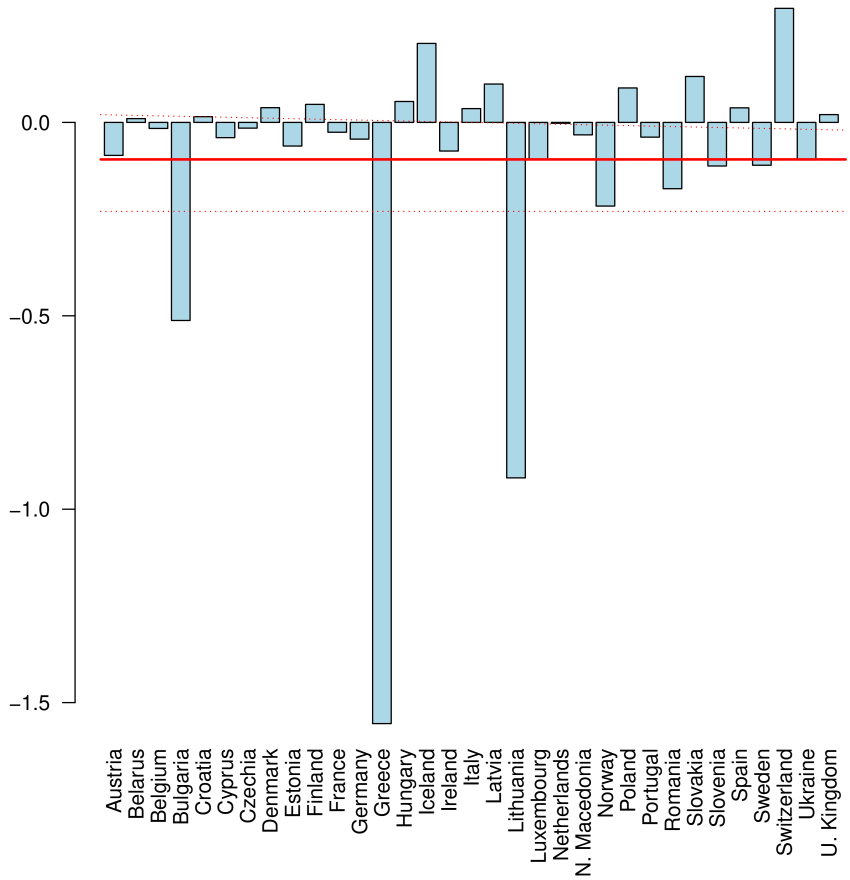
However, country-by-country estimates reveal that $\varepsilon^{Long-run}_{GDP,REC}$ is empirically zero for those countries around the estimated turning point between CO2 and GDP, such as France, and Spain.

The European Union could act as an intergovernmental agency to rigorously promote economic growth and investment in the sustainable energy sector, especially in the Eastern nations, to reinforce the development of cleaner energies and promote the decarbonization path. Achieving the objectives of the Agenda 2030 represents a fundamental step to begin evaluating the effectiveness of the economic policies implemented by States and evaluating how to best integrate renewable infrastructures in Eastern Europe.

The "sustainable degrowth" hypothesis applies to those countries with an undeveloped renewable energy infrastructure and in a relative de-copulation path (before the turning point), mainly Eastern European countries (Bulgaria, Greece, Lithuania, Romania, Slovakia, Slovenia). Governments dealing with this dilemma should contemplate adopting a multifaceted approach. This strategy aims to concurrently reduce pollutant gas emissions, promote renewable energy consumption, and sustain positive economic growth through targeted subsidies. Additionally, stringent control over fossil energy usage is crucial, and a carbon tax setting could facilitate a transition toward a low-carbon economy, ultimately fostering environmental improvement.

The sustainable degrowth hypothesis

To understand the factors of the negative effect of RECs on GDP, we disentangle the role of environmental policies on economic growth. Figure 2.10 indicates the total number of national renewable energy policies since the Paris Agreement (2015). This indicator highlights how the relevance of environmental policies has increased. However, it does not consider the stringency or quality of these policies. In particular, given the "sustainable degrowth" hypothesis, we want to test whether the quality of environmental policies affects renewable energy consumption and economic growth.



Note: The continous red line is the average coefficient reported in Table 2.7 column 9 while the dotted red lines are the confidence bands for the average coefficient.

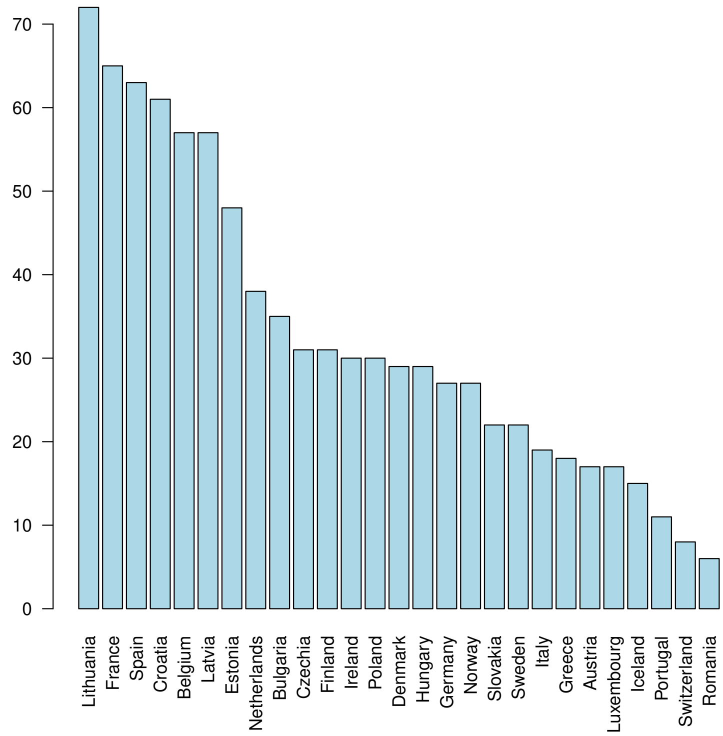
Figure 2.9: Country-by-country estimation of REC coefficients in Eq. (2.36)

To determine the role of environmental policies, we incorporate the OECD Environmental Policy Stringency (EPS)[16] index in the DCCEMG estimation. This index is a country-specific and internationally comparable measure of environmental policy stringency, reflecting the extent to which these policies impose an explicit or implicit price on polluting or environmentally harmful behavior. It is based on 13 environmental policy instruments related to climate and air pollution, ranging from 0 (indicating no stringency) to 6 (representing the highest degree of stringency).[17]

Table 2.9 presents the EPS coefficients. While in the short term, the role of EPS is not relevant for both GDP and REC, except for its lag for REC, it is significant in the

[16] https://stats.oecd.org/Index.aspx?DataSetCode=EPS.

[17] We did not consider this variable in the general analysis since this is not available for the entire panel but is used now to investigate the role of environmental policies in this context, accordingly we excluded: Belarus, Bulgaria, Croatia, Cyprus, Estonia, Iceland, Latvia, Lithuania, North Macedonia, Romania, Ukraine.



Source: European Environment Agency

Figure 2.10: Number of sustainable energy policies post Paris Agreement (2015).

	$\ln\ GDP_t$	$\ln\ REC_t$
Short-run		
EPS_t	0.00962	-0.0887
	(0.0146)	(0.116)
EPS_{t-1}	0.0127	-0.0525*
	(0.0208)	(0.0262)
$\ln\ REC_{t-1}$	-0.0127	-0.0873
	(0.0312)	(0.149)
$\ln\ REC_t$	-0.0394	
	(0.0350)	
Long-run		
EPS	-0.0554*	-0.281*
	(0.0317)	(0.155)
$\ln\ REC$	-0.0591	
	(0.0436)	

Note: Dynamic CCEMG estimation of Equations (2.34) and (2.36) with the additional consideration of EPS index. Full estimations with control variables are available upon request.

Table 2.9: DCCEMG Estimation of EPS effect on GDP and REC

long run, thus emphasizing the importance of environmental policies in the long term, thereby confirming the need to consider this factor when formulating these policies.

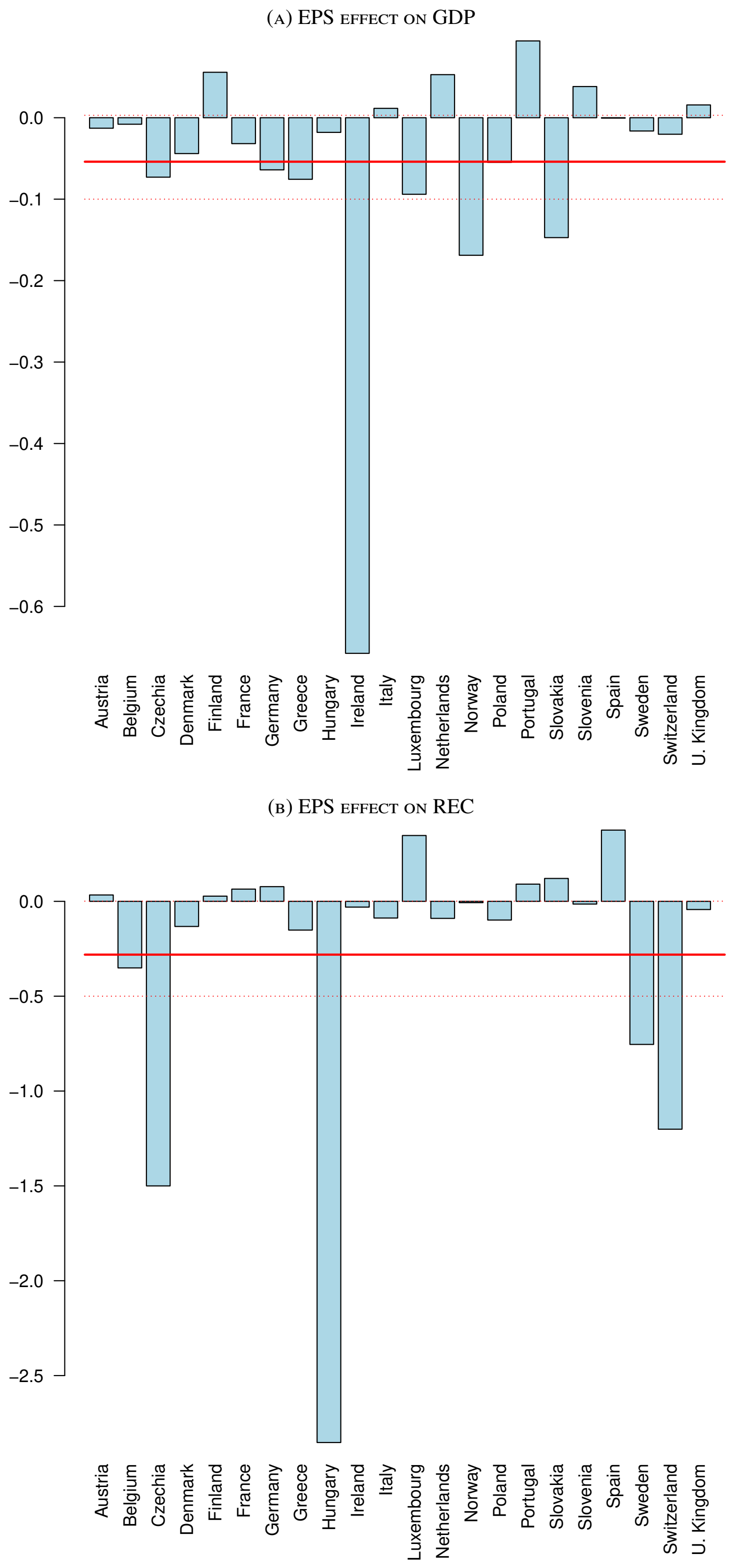
Considering the EPS variable leads to the REC coefficient becoming statistically zero. This result implies that the stringency of environmental policies plays a crucial role in shaping the relationship between renewable energy consumption and economic growth.

Figure 2.11 shows country-by-country coefficients of the long-run effect of EPS on GDP (panel A) and REC (panel B). In the EPS-GDP case, the country coefficients are almost similar to the average value in Table 2.9, except Ireland, which shows a relatively higher coefficient. According, Botta and Koźluk (2014) claim how the stringency of Ireland's environmental policies is the lowest in the sample since it aims to develop other alternative economic policies to improve capital inflows after the 2012 debt crisis (taxes easiness), directly affecting its economic growth. Therefore, the effect of environmental policies can harm economic growth because environmental policies have not played a significant role in the industrial context of the country in recent years. Furthermore, controlling greenhouse gas emissions could influence the production dynamics of those companies not accustomed to using clean energy, with a detrimental effect on wealth.

In the EPS-REC case, while the average value is negative and significant, we found several interesting results from Figure 2.11. For those countries with a developed renewable energy infrastructure, such as Spain, the EPS stimulates the use of REC, as reported in Marra and Colantonio (2021) and Hassan et al. (2024). In these countries, EPS is a positive factor for economic growth, emphasizing how the integration of these energies promotes economic growth in the long term. Our results do not confirm the "sustainable degrowth" hypothesis for the wealthier countries of the sample. Magazzino et al. (2022) obtained the same results for a panel of Scandinavian countries.

In contrast, a significant detrimental effect of EPS on REC is found in the Czech Republic and Hungary, which need to improve their environmental standards to align with other European countries, as highlighted by Bashir et al. (2022). The divergence from the literature also lies in the fact that previous studies investigate the aggregate role of EPS without enlarging the discussion to the countries within the panel.

In some cases, such as France, Germany, and Italy, the EPS impact on REC is not significant. This observation aligns with the three economic stages discussed in



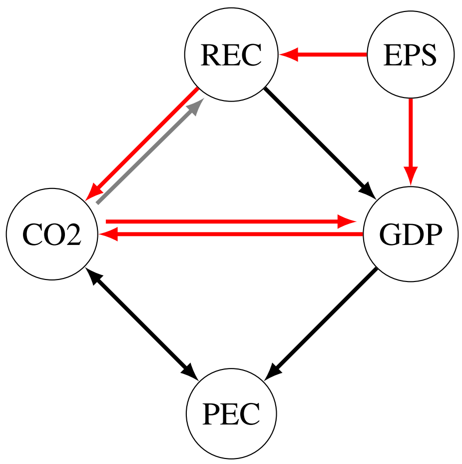
Note: The continous red line is the average coefficient reported in Table 2.9, while the dotted red lines are the confidence bands for the average coefficient.

Figure 2.11: Country-by-country long-run estimation of EPS impact on GDP and REC respectively, Table 2.9.

Grossman and Krueger (1991), placing these countries in the industrialization phase, nearing the post-industrialization period. Consequently, there is a heightened social awareness among governmental bodies and economic actors despite the renewable infrastructure development process.

2.4.4 Causality analysis

To ensure the robustness of our results and broaden the economic discussion, we perform Granger Causality (GC) analysis following Dumitrescu and Hurlin (2012) (DH). Unlike other studies that employ non-stationary time series for the DH test (or do not specify variable integration),[18] we take the first difference of the non-stationary variables to avoid spurious results as underlined by hypothesis A3 of the DH test (stationary covariance). The detailed statistics of the $\tilde{Z}$ test with the corresponding bootstrap p-values for cross-sectional dependence for the main variables can be found in Table 2.10, while Figure 2.12 reports the directional results.



Note: The red arrows indicate a p-value of 1%, the black arrows mean a p-value of 5% and the grey arrow refers to a p-value of 10%

Figure 2.12: Granger Causality directions across main variables

The results in Figure 2.12 confirm Miller and Russek (1990), which suggests that Granger Causality (GC) must exist in at least one direction when two variables are cointegrated. Although we have not reported the estimate of Primary Energy Consumption (PEC) in Table 2.7, we take advantage of this additional analysis to test the

[18] See, among others, Balsalobre-Lorente et al. (2022) and Usman and Balsalobre-Lorente (2022).

four causality hypotheses discussed in Table 2.1. Since we find a unidirectional effect from GDP to PEC, we validate the conservation hypothesis.

REC predicts CO2, confirming the Dynamic CCEMG results. Considering this result with that of the Table 2.7 we can underline how the role of REC has a significant contemporary effect on carbon dioxide emissions. Furthermore, we could say that there is no sort of carry over effect (the coefficient REC_{t-1} is not significant) in this case. The causality from GDP to CO2 is also relevant for establishing the role of economic growth on environmental degradation. We confirm the bidirectional relationship between GDP and CO2, as reported in Dogan and Seker (2016). Notably, a unidirectional causality emerged from REC to GDP, corroborating the validity of the sustainable degrowth hypothesis. We demonstrate a feedback hypothesis at 10% between REC and CO2, confirming Saidi and Omri (2020), Ahmad et al. (2021), and Magazzino et al. (2022).

Furthermore, we find a unidirectional causality environmental policy stringency to renewable energy consumption, as Hassan et al. (2024) reported. To conclude, the role of EPS on GDP is also confirmed by the causality test.

	$\tilde{Z}$
PEC does not GC CO2	7.21 **
CO2 does not GC PEC	8.35 **
REC does not GC CO2	12.679 ***
CO2 does not GC REC	5.214
GDP does not GC CO2	14.04 ***
CO2 does not GC GDP	5.144 ***
PEC does not GC GDP	2.97
GDP does not GC PEC	4.49 *
REC does not GC GDP	4.127 **
GDP does not GC REC	1.98
GDP does not GC EPS	0.75
EPS does not GC GDP	13.00 ***
REC does not GC EPS	2.10
EPS does not GC REC	15.60 ***

*5% $< p <$ 10%,** 1% $< p <$ 5%,*** $p <$ 1%

Table 2.10: DH test, $\tilde{Z}$

2.5 Conclusions

This study focuses on European countries that faced significant economic and political transformations, particularly during and after the 1990s. Preliminary, we test for slope heterogeneity and spatial cross-dependence, followed by unit root tests and cointegration analysis. Our results revealed the presence of heterogeneity and cross-sectional dependence in the samples, with the main variables cointegrated. Subsequently, we estimate a Cross-Sectional Autoregressive Distributed Lgs (CS-ARDL) model via the Dynamic Common Correlated Effect Mean Group (DCCEMG) estimator. This technique is robust in the presence of slope heterogeneity and cross-dependence in the data, while it allows for considering long-run relationships.

Based on the control variable used determined following the existing literature, we investigate the CO2 determinans. Then, we enlarge the discussion between economic growth and Renewable Energy Consumption (REC).

We found a non linear relationship between environmental degradation (CO2) and economic growth (GDP), discussing the different decoupling stages across European countries. Our main findings indicate that REC reduces air pollutant emissions, especially in the long run, aligning with the existing literature. However, it is noteworthy that the average effect of renewable energy consumption reduces GDP in Eastern European countries, particularly in the long period, thus aligning with the sustainable degrowth theory.

Finally, we include the Environmental Policy Stringency (EPS) index to understand the role of environmental government policies in influencing economic growth. Similarly, our analysis reveals an aggregate negative effect on per capita GDP and REC. However, when analyzing the country-by-country coefficients, we found several interesting results. The adverse impact of environmental regulations is particularly pronounced for the economies of Eastern Europe, especially considering their relatively underdeveloped renewable energy infrastructure compared to other countries.

The validity of the non linear relationship between CO2 and GDP, combined with EPS-REC country-by-country results, highlights three considerations. First, Eastern European countries are in a phase of relative decoupling from the rest of European nations. In these Eastern countries, environmental policies damage economic growth and the REC since the general renewables infrastructure is weak. This situation is in line with the hypothesis of sustainable degrowth. Second, industrialized countries (such as France, Italy, and Portugal) have a marginal role of environmental policies for renewable energy consumption and economic growth. Third, for economies where renewable energy consumption is well integrated into the country's energy mix (France – nuclear, Netherlands – wind, Spain – wind/solar), environmental policies promote the growth of renewable energy and the national economy.

From a policy point perspective, the negative relationship between environmental policies and renewable energy shows that Eastern European countries should promote a green financial system, thus attracting capital inflows into such projects (Irandoust, 2019; Saud et al., 2019). Furthermore, these countries need to focus on market rules when subsidies are not enough to promote the integration of renewable energy. Finally, it is essential to streamline bureaucratic procedures, encourage investment in research and development, and facilitate the efficient operation of patents and licenses in the market.

In contrast, for those richer countries where environmental policies improve economic growth and renewable energy consumption, economic policies to implement are considerably easier. In particular, given the substitutability effect of renewable energy compared to dirty energy, when these technologies are well integrated into markets, the presence of energy taxes and renewable energy certificates as market-based policies has a positive effect on the development of renewable energy (Karmaker et al., 2021; Zhu et al., 2022). Furthermore, the positive role of EPS on REC and GDP underlines the value of non-market environmental policies, such as limiting carbon emissions in the transport sector, to develop hybrid/electric technologies that could reduce emissions and be more convenient for all the economic actors (Da Rosa and Ordóñez, 2021).

Future research can assess the weak exogeneity properties of the primary regressors by reevaluating the baseline model specification using a Panel Error Correction Model representation. As discussed in Urbain (2012) and Nicolau and Palomba (2015), this approach allows researchers to determine whether conditioning the model on certain variables preserves significant information. From an economic point of view, it could be interesting to repeat the analysis for different geographical areas, such as South America and China, given their different developments in renewable energy usage.

2.A Environmental Kuznets Curve

In terms of the relationship between carbon emissions and renewable energy consumption, a large part of the literature focuses on the relationship between energy consumption (degradation) and economic growth. On the opposite side of the Environmental Kuznets Curve is the so-called "growth limit theory." This field of study originated from the viewpoint of the economists of the Rome Group, whose studies affirmed how economic development cannot proceed indefinitely due to the insufficient availability of extracted natural resources. This branch of analysis considered an N-shaped association between production and pollution. However, the N-shaped curve was empirically tested, and the results showed the non-significance of this hypothesis (Gyamfi et al., 2021).

The EKC was introduced into the literature by Grossman and Krueger (1995), who defined how environmental degradation is promoted by fiscal expansion and economic growth. In their pioneering work, Grossman and Krueger (1995) introduced three types of effects in the inverted U-shaped relationship linking environmental degradation to economic growth. In Figure 2.13, these three situations are highlighted:

1. *Scale effect*: the market for natural resources increases in significance as economic developments come through the use of these elements that are converted in the production cycle. In this state of production, companies begin to produce more and more products, increasing the total amount of toxic chemical gases. In this situation, to promote economic growth, governments neglect to reduce pollutant gas emissions, and as a result, ecological damage increases as economic development increases. We are in the increasing part of the nonlinear function depicted in Figure 2.13. This phenomenon is more pronounced if the market is based mainly on dominant and complementary fields.

2. *Structure effect*: economic development evidenced during the scale effect leads to an increase in wages. As the market structure influences the development of economic growth, the increase in wages leads to a more socially concerned population. At this stage, the shape of the curve begins to change. When the

maximum degradation level has been reached, and people recognize the possibility of a natural disaster, it starts to decrease.

3. *Technique effect* implies that companies begin to revise the production way by using more sustainable technologies that increase efficiency. It implies that the tertiary sector begins to improve, and the business environment gradually goes to be information-intensive rather than wealth-intensive. All these elements lead the central government to spend more on innovation and production-based operations, replacing polluting technologies with more sustainable systems.

Many studies have investigated this model, and the literature has not reached a mutual closure. A recent review of methods can be found in Koondhar et al. (2021) and Pincheira and Zuniga (2021). Several control variables have been used in this type of literature, mainly to avoid the problem of endogeneity. The most recent and cited works are given in Table 2.11, with identification of the sample and the relevant methods used. The various studies involved different times and samples, but we can say that most of the investigations do not reject the EKC hypothesis.

Furthermore, according to Mikayilov et al. (2018), when emissions grow less rapidly than GDP, environmental economists express the concept of relative decoupling; if emissions even decrease relative to the pace of economic growth, then decoupling is absolute (see Figure 2.14).

Authors	Methodology	Sample/countries	Time-span	EKC Results
Ahmad et al. (2021)	Long panel	OECD	1990-2014	Confirmed
Ummalla and Goyari (2021)	Long panel	BRICS	1992–2014	Confirmed
Pontarollo and Mendieta Muñoz (2020)	Spatial Bayes Panel	221 Ecuador's cantons	2007-2015	Not-Confirmed
Arshad Ansari et al. (2020)	Long panel	37 Asian countries	1991-2017	Confirmed
Dogan et al. (2020)	Long panel	BRICST	1980-2014	Not-confirmed
Halliru et al. (2020)	Long panel quantile	6 West African countries	1970-2017	Not-confirmed
Pontarollo and Serpieri (2020)	Spatial panel	42 Romanian econ.	2000-2014	Confirmed
Usama et al. (2020)	ARDL	Ethiopia	1981-2015	Confirmed
Ridzuan et al. (2020)	ARDL	Malaysia	1978-2016	Not-confirmed
Aydin and Turan (2020)	Long panel	BRICS	1996-2016	Confirmed
Boubellouta and Kusch-Brandt (2020)	GMM-TSLS	30 EU	2000-2016	Confirmed
Dogan and Inglesi-Lotz (2020)	Long panel	EU	1980-2014	Confirmed
Zhang et al. (2019)	Pooled OLS	121 countries	1960-2014	Confirmed
Yilanci and Ozgur (2019)	Bootstrap methods	G7 countreis	1970-2014	Not-confirmed
Usman et al. (2019)	VECM	India	1971-2014	Confirmed
Haseeb et al. (2018)	Long panel	BRICS	1995–2014	Confirmed
Abdouli et al. (2018)	Pooled OLS	BRICST	1990–2014	Confirmed
Sarkodie (2018)	Long panel	17 African countries	1971-2013	Confirmed
Bakirtas and Cetin (2017)	Panel VAR	5 countries	1982-2011	Not-confirmed
Hanif and de Santos (2017)	FE model	86 dev. countries	1972-2011	Confirmed
Antonakakis et al. (2017)	Panel VAR-IRF	106 countries	1971–2011	Not-confirmed
Al-Mulali and Ozturk (2016)	VECM	27 dev. countries	1990-2012	Confirmed
Al-Mulali et al. (2015)	GMM	High income countries	1980–2008	Confirmed
Kasman and Duman (2015)	Long panel	EU countries	1992–2010	Confirmed
Azlina et al. (2014)	VECM	Malaysia	1975-2011	Not-confirmed
Pao and Tsai (2011)	VECM	BRICS	1992-2007	Confirmed
Pao et al. (2011)	Johansen coint.	Russia	1990-2017	Not-confirmed
Acaravci and Ozturk (2010)	ARDL	India	1971-2014	Not-confirmed
Apergis and Payne (2009)	IPS, Pedroni coint.	Central America	1971–2004	Confirmed

Note: *Confirmed* states that EKC is valid for at least 80% of the panel. For *long panel* we meant Pooled Mean Group Estimator, FMOLS, DOLS and panel cointegration methods. For an older EKC review see Dogan and Seker (2016) and Bilgili et al. (2016).

Table 2.11: Recent selected literature Review on EKC.

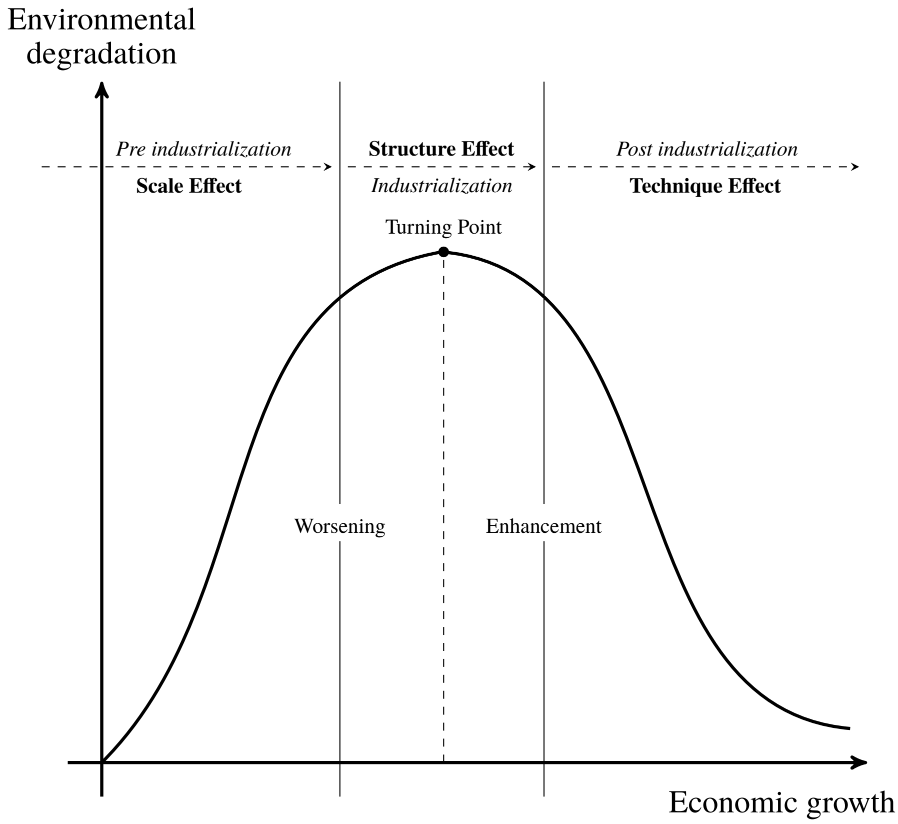


Figure 2.13: EKC curve.

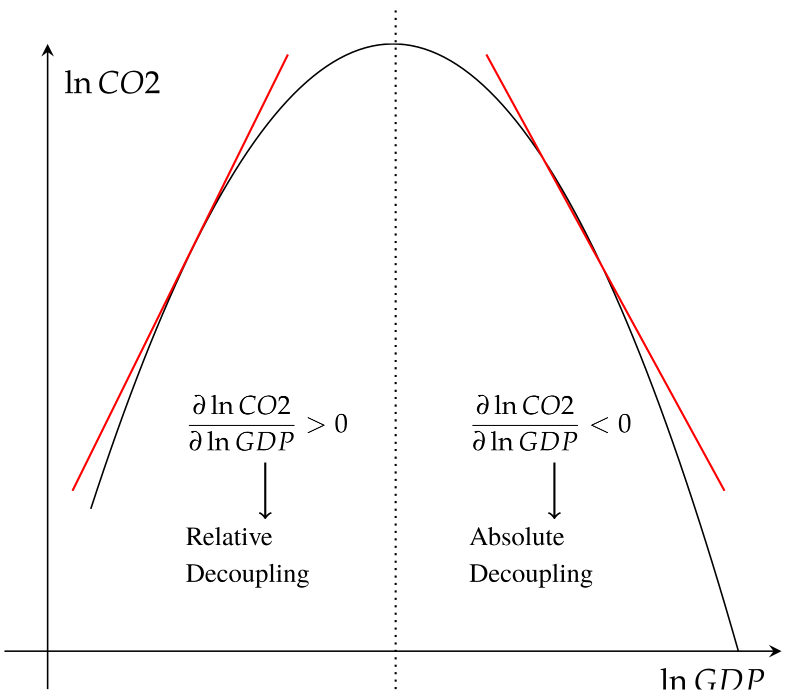


Figure 2.14: EKC and decoupling theory

2.B Panel Cointegration methodology details

Group-mean

Group-mean tests are based on the equation (2.16) in which the (V)ECM representation is given. Group mean tests can be constructed in three steps. First, it is essential to estimate the parameters of the equation (2.16) to least squares for each unit i, thus obtaining:

$$\Delta y_{it} = \hat{\delta}_i' d_t + \sum_{j=1}^{P} \hat{\phi}_{ij} \Delta y_{i,t-j} \sum_{j=1}^{Q} \hat{\beta}_{ij} \Delta x_{i,t-p} - (1 - \hat{\phi}_i)[y_{it-1} - \hat{\beta}_i x_{it-1}] \tag{2.38}$$

where the lag and advance orders, P and Q, can vary among individuals and can preferably be determined using a data-dependent rule. From the estimate, one can also obtain the estimated error terms $\hat{\varepsilon}_{it}$ which, together with $\hat{\beta}$, are used to compute the long-run variance estimators Newey and West (1994):

$$\hat{u}_{it} = \sum_{j=-Q}^{P} \hat{\beta}_{ij} \Delta x_{it-j} + \hat{\varepsilon}_{it}. \tag{2.39}$$

Considering $\hat{u}_{it}$ for calculating Newey's variance-covariance matrix and West ω_u, define $\hat{y}_{it}$ for estimating ω_y. The ratio of ω_u to ω_y gives the estimated value of $\phi_i(1)$. This estimation procedure does not take into account any deterministic terms. To correct for this, Δy_{it} in $\omega_{y_i}^2$ must be replaced by the fitted residuals of a first-order regression of Δy_{it} on the deterministic d_t part. Finally, tests of the group mean are calculated as follows:

$$G_\tau = \frac{1}{N} \iota' \left(\frac{\hat{\phi}_i}{SE(\hat{\phi}_i)} \right) \quad \text{and} \quad G_\phi = \frac{T}{N} \iota' \left(\frac{\hat{\phi}_i}{\hat{\phi}_i(1)} \right) \tag{2.40}$$

Panel test

As for the panel test, the procedure is divided into three parts. First, to obtain the estimated coefficients, it is necessary to define a regression of Δy_{it} and y_{it-1} on the deterministic part, the deltas of y and the lagged value of x:

$$\begin{cases} \Delta\tilde{y}_{it} = \Delta y_{it} + \hat{\delta}_i' d_t + \hat{\beta}_i' x_{it-1} - \sum_{j=1}^{P} \hat{\phi}_{ij} \Delta y_{it-j} + \sum_{j=1}^{Q} \hat{\beta} x_{it-j}, \\ \tilde{y}_{it-1} = y_{it-1} + \tilde{\delta}_i' d_t + \tilde{\beta}_i' x_{it-1} - \sum_{j=1}^{P} \tilde{\phi}_{ij} \Delta y_{it-j} + \sum_{j=1}^{Q} \tilde{\beta} x_{it-j}. \end{cases} \tag{2.41}$$

The fitted values of $\Delta\tilde{y}_{it}$ and $\tilde{y}_{it-1}$ are then used for computing the *Common Error Correction Parameter* (CECP), $\hat{\phi}$:

$$\hat{\phi} = \left(\tilde{\boldsymbol{y}}'\tilde{\boldsymbol{y}}\right)^{-1} \left(\frac{\tilde{\boldsymbol{y}}'\Delta\tilde{\boldsymbol{y}}}{\boldsymbol{\iota}'\hat{\phi}_i}\right), \tag{2.42}$$

where $\boldsymbol{\iota}$ is the vector of ones, ϕ_i and $\tilde{\boldsymbol{y}}$ are obtained from Eq (2.41) and expressed as vectors. In the second stage, the significance of the parameter must be computed. The standard error follows the estimated coefficients $\tilde{y}^2_{it-1}$ and the value of $\hat{\phi}$:

$$SE(\hat{\phi}_i)^2 = \boldsymbol{\Theta}^{-1} \left(\tilde{\boldsymbol{y}}'\tilde{\boldsymbol{y}}\right), \quad \text{with:} \quad \boldsymbol{\Theta} = \frac{\hat{\boldsymbol{\varepsilon}}'\hat{\boldsymbol{\varepsilon}}}{N(\boldsymbol{\iota}'\hat{\phi})}, \tag{2.43}$$

with $\hat{\varepsilon}$ being the vector of standard error from Eq. (2.38). The third, and last step, is to determine the statistics dividing the estimated value of the CECP by its standard deviation:

$$P_\tau = \frac{\hat{\phi}}{SE(\hat{\phi})} \quad \text{and} \quad P_\phi = T\hat{\phi}. \tag{2.44}$$

Asymptotic distribution of tests

For both tests, panel and mean-group, the asymptotic distribution is based on sequential limit theory, in which T goes to infinity before N. Consequently, the tests are justifiable for a large T. We define $W_i^d(r)$ with $r \in [0,1]$ as a vector formed by t, the limiting trend function, $V_i(r)$ and $W_i(r)$ the standard scalar and K-dimensional, independent Brownian motions, respectively. A Brownian motion is a continuous stochastic real-valued process introduced by Norbert Wiener in which the unconditional probability density function follows a normal distribution with zero mean and variance t. Then let $U_i(r)$ and the vectors $B_i(r)$ and $\tilde{B}_i(r)$ be defined as follows:

$$U_i(r) = V_i(r) - \left(\int_0^1 V_i(r)(W_i^d(r))'\right)\left(\int_0^1 W_i^d(r)(W_i^d(r))'\right) W_i^d, \tag{2.45}$$

$$B_i(r) = \left(\int_0^1 U_i^2(r), \int_0^1 U_i(r) dV_i(r) \right)', \tag{2.46}$$

$$\tilde{B}_i(r) = \left(\frac{\int_0^1 U_i(r) dV_i(r)}{\int_0^1 U_i^2(r)}, \frac{\int_0^1 U_i(r) dV_i(r)}{\sqrt{\int_0^1 U_i^2(r)}} \right). \tag{2.47}$$

By indicating with η and $\tilde{\eta}$ the mean values of $B_i(r)$ and $\tilde{B}_i(r)$, and with Σ and $\tilde{\Sigma}$ their variance, the test has the following asymptotic distribution:

$$\mathbf{H}_j - \sqrt{N}(\boldsymbol{\eta}_j^H) \rightarrow N(0, \boldsymbol{\Sigma}_j^h), \tag{2.48}$$

where $\mathbf{H} = (\sqrt{N}G_\phi, \sqrt{N}G_\tau, \sqrt{N}P_\phi, P_\tau)$ is the vector of tests,

$$\boldsymbol{\eta}^H = (\tilde{\eta}_1, \tilde{\eta}_2, \frac{\eta_2}{\eta_1}, \frac{\eta_2}{\sqrt{\eta_1}}), \quad \text{and} \quad \boldsymbol{\Sigma}^H = (\tilde{\Sigma}_{11}, \tilde{\Sigma}_{22}, \alpha' \Sigma \alpha, \theta' \Sigma \theta) \tag{2.49}$$

are the associated mean and variance vectors with:

$$\alpha = \left(-\frac{\eta_2}{\eta_1^2}, \eta_1^{-1} \right)' \quad \text{and} \quad \theta = \left(-\frac{\eta_2}{2\sqrt{\eta_1}^3}, \frac{1}{\sqrt{\eta_1}} \right)'. \tag{2.50}$$

The values are then compared with the left tail of the normal distribution: high negative values imply rejection of the null hypothesis. The bootstrap technique is used to account for cross-sectional dependence.

2.C Panel time series representation

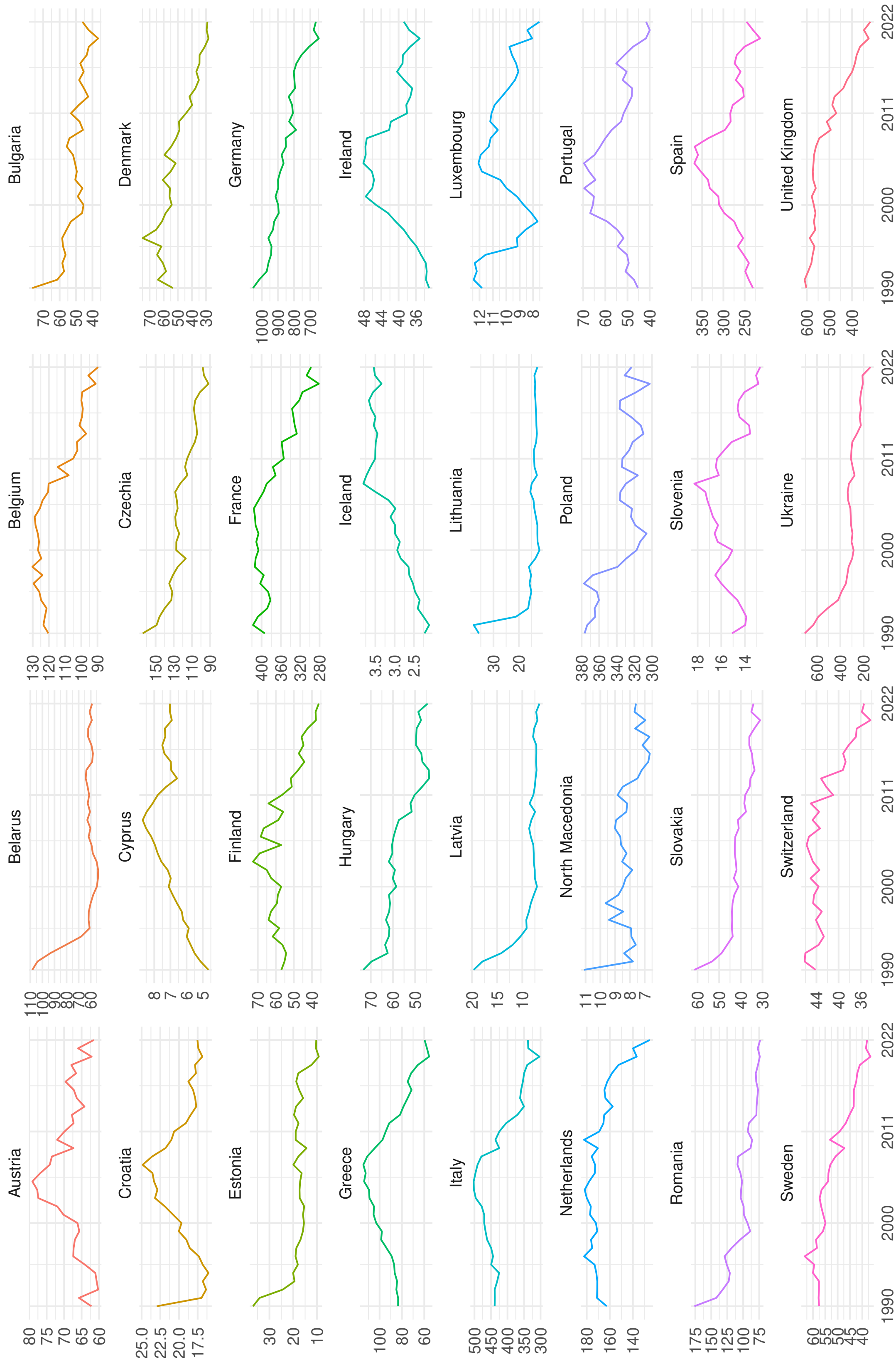


Figure 2.15: Carbon Dioxide Emissions

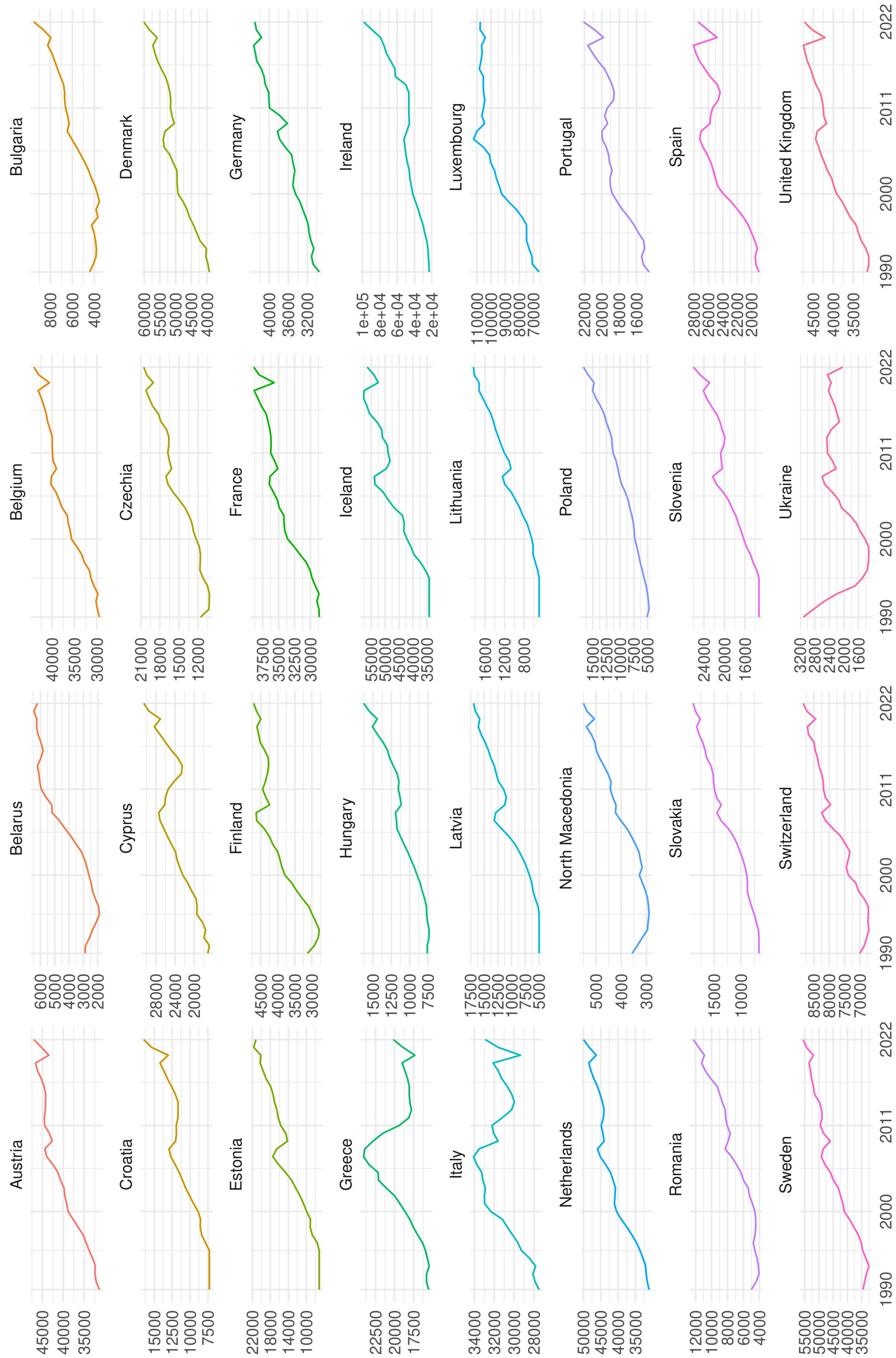


Figure 2.16: GDP per capita (2015 US$)

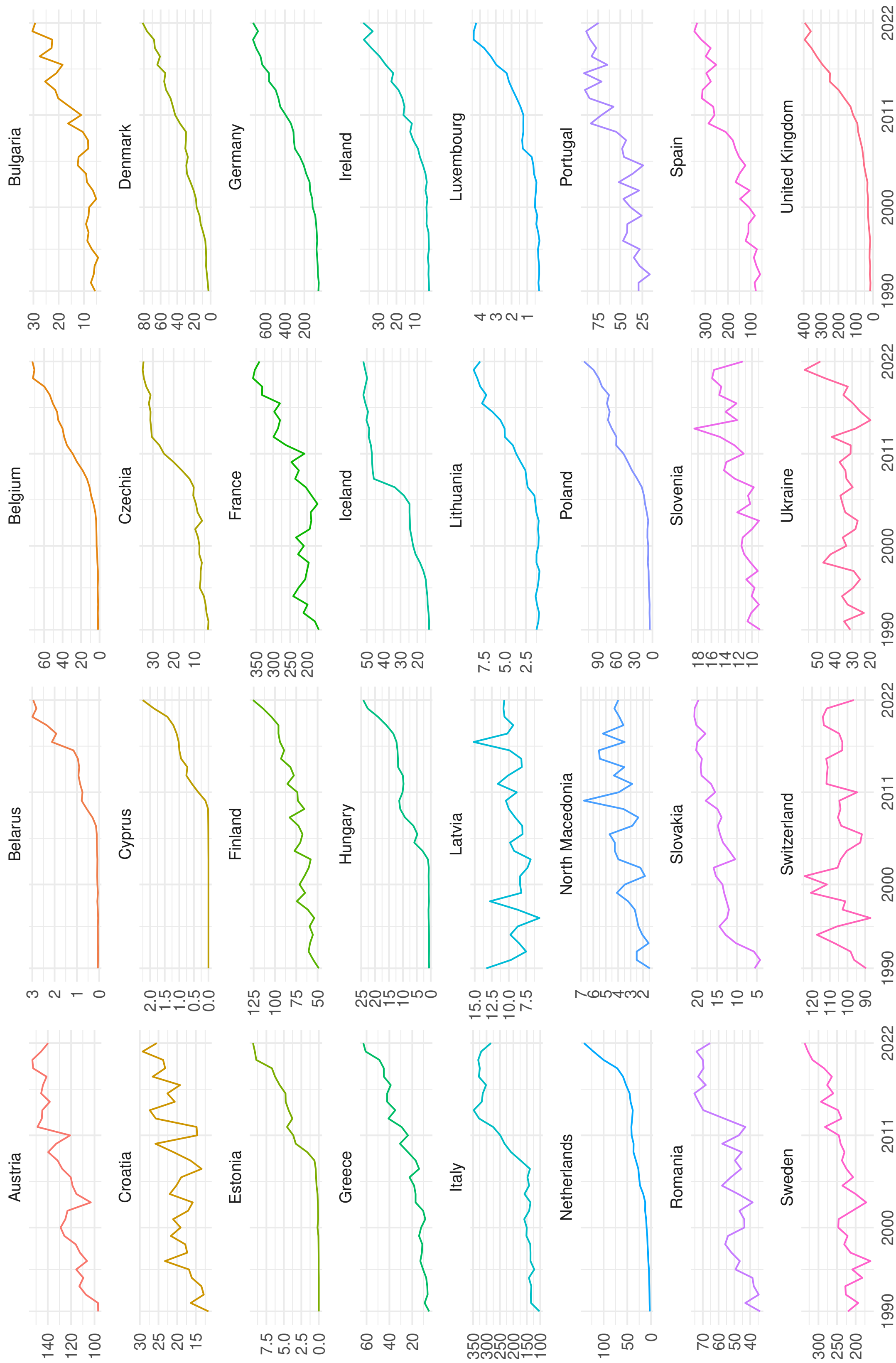


Figure 2.17: Renewable Energy Consumption

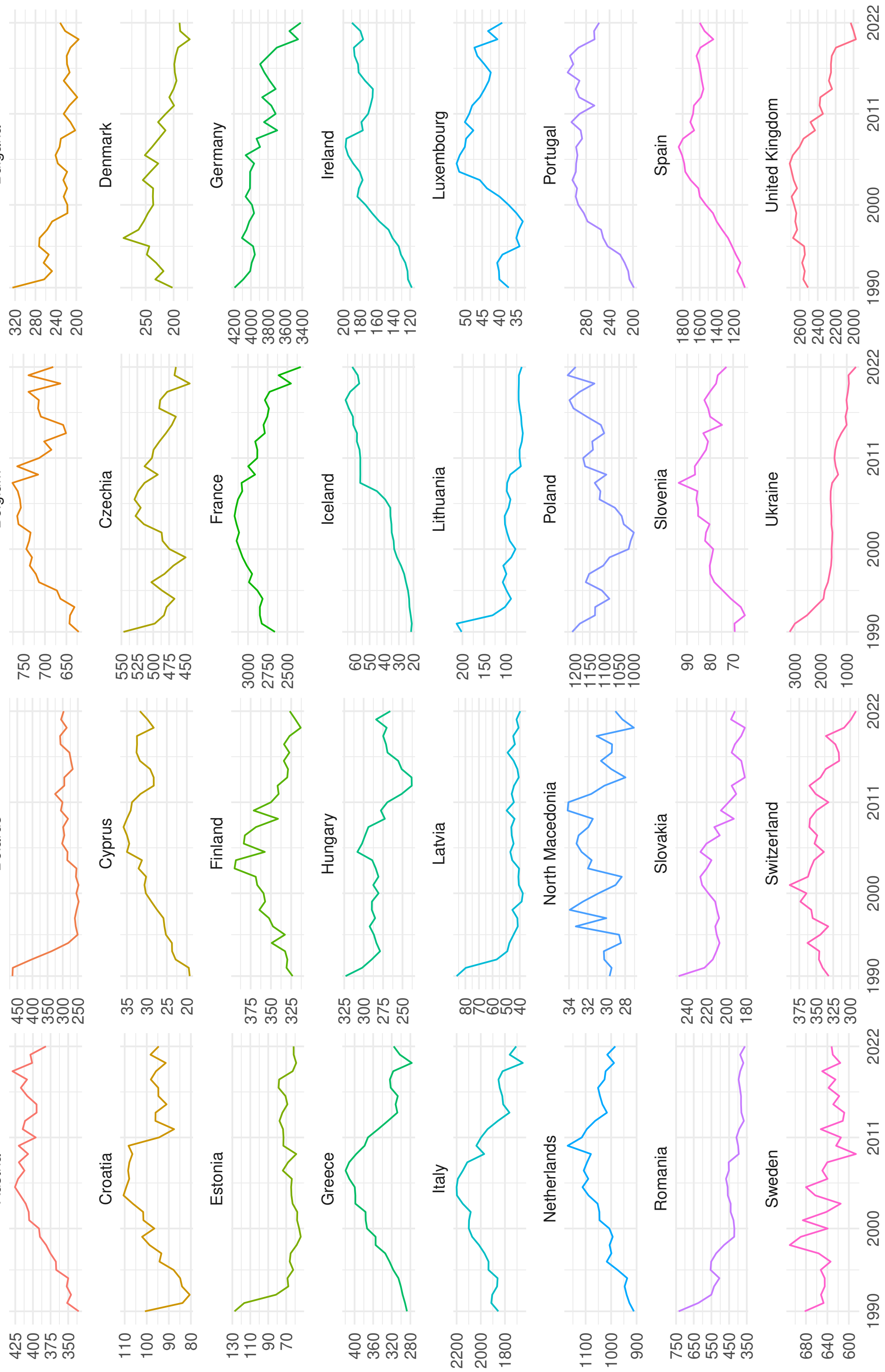


Figure 2.18: Primary Energy Consumption

2.D Panel renewable energies representation

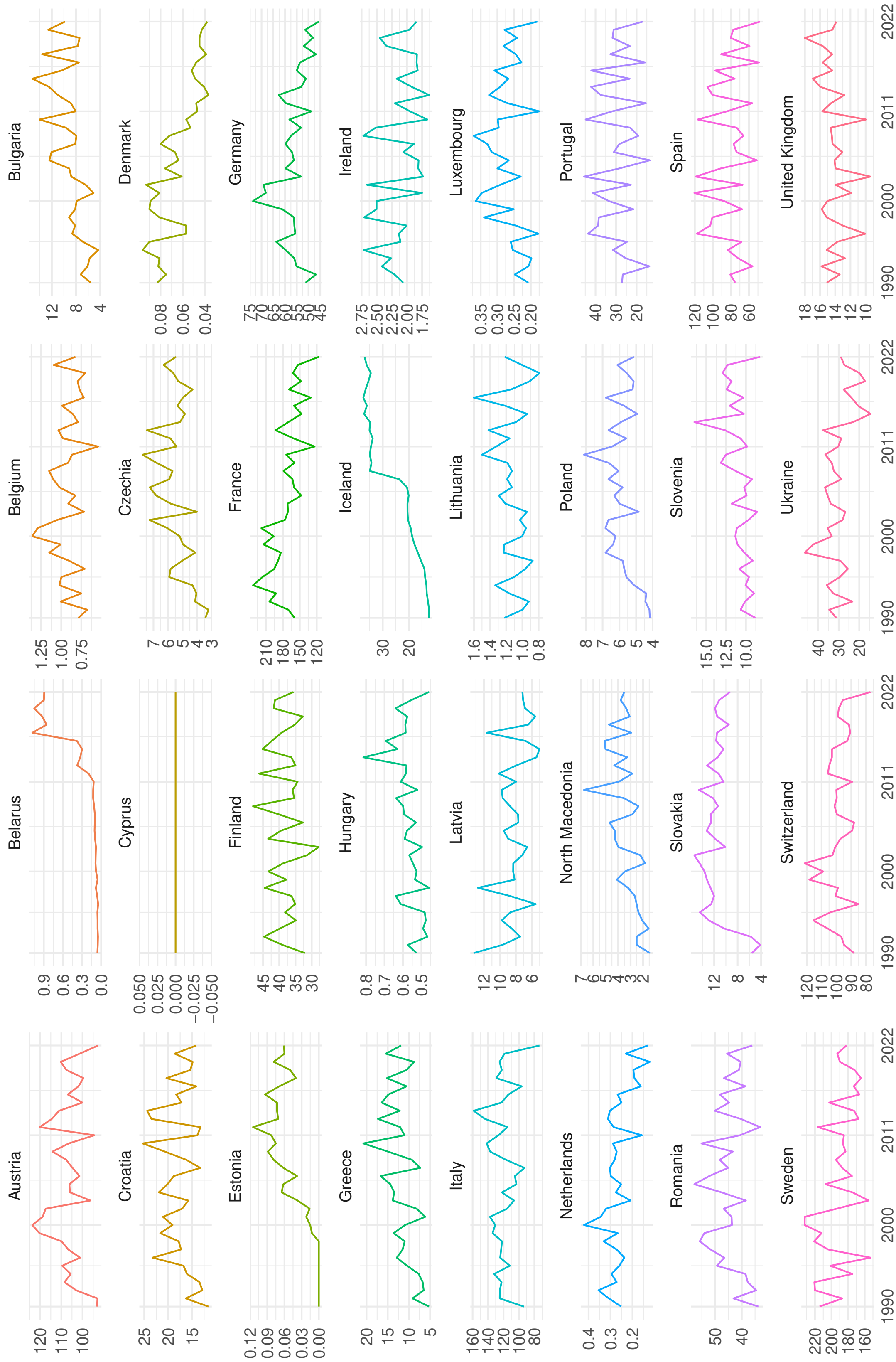


Figure 2.19: Hydroelectric Consumption

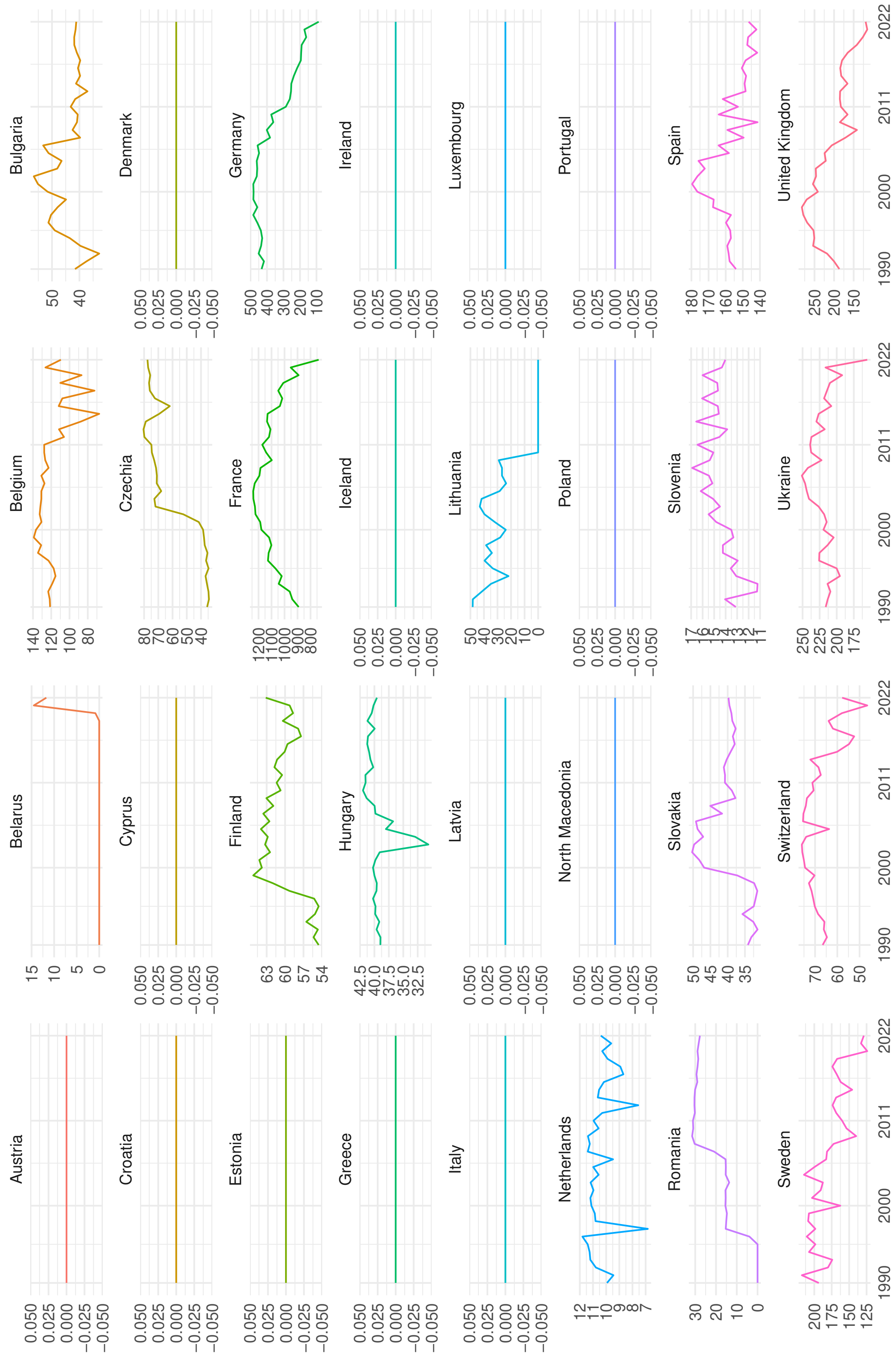


Figure 2.20: Nuclear Consumption

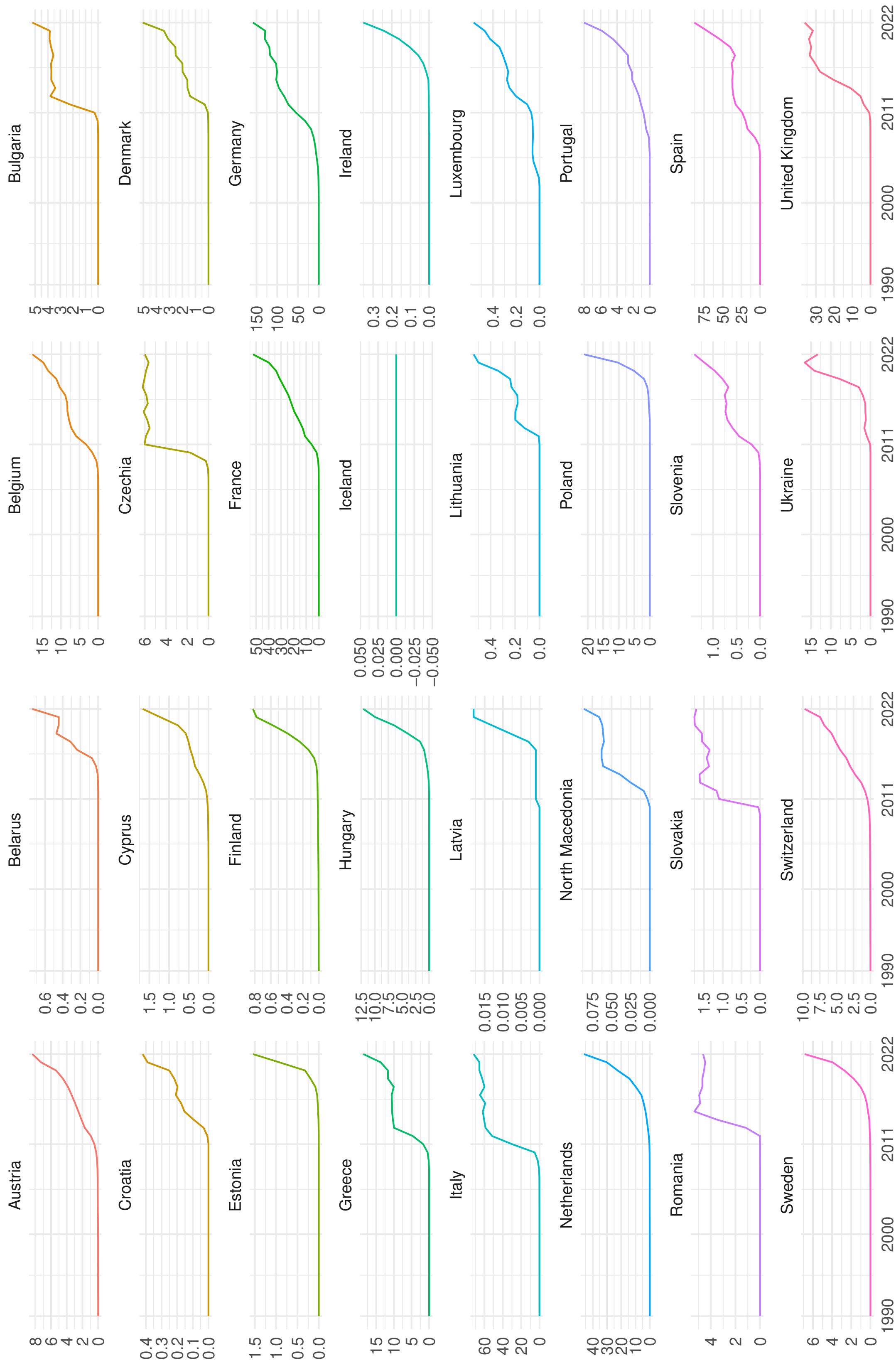


Figure 2.21: Solar Consumption

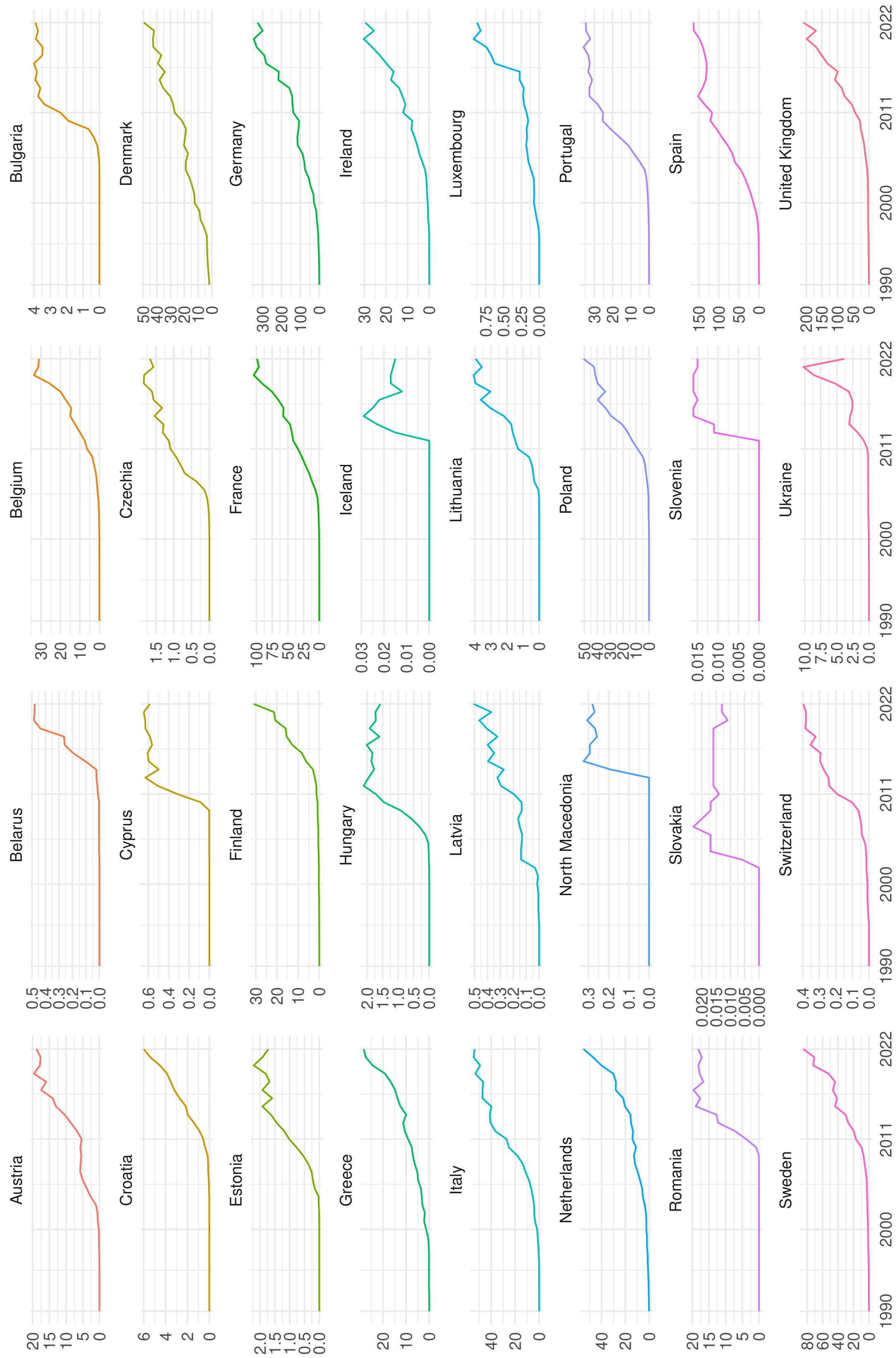


Figure 2.22: Wind Consumption

Chapter 3

The role of temperature in natural gas demand and the recent inflation surge. An Eurozone perspective.

Abstract

The impact of global warming on the current economies is getting heavier. To account for this development, we employ a Time-Varying Parameter Vector Autoregression (TVPVAR) model to investigate whether the decrease in European gas demand is ascribable to the gas price increase (especially after the Russia-Ukraine conflict) or is a global warming consequence. Using monthly data from January 2015 to September 2023, we show the relevant role of average temperature in the demand contraction. Moreover, through a wavelet coherence analysis approach, we study the role of temperature and geopolitical risk in the current European inflation surge, confirming that higher temperatures have partially contained the increase in energy inflation. Our results provide some policy recommendations for policymakers and governments.

3.1 Introduction

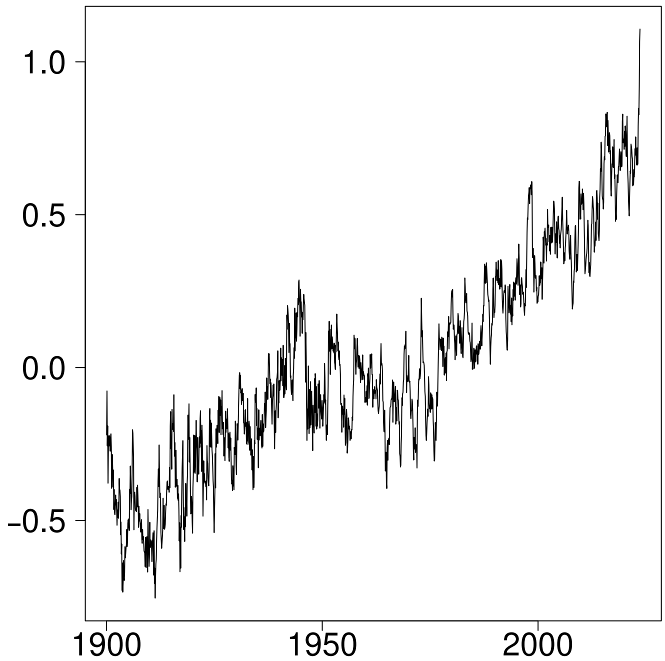
Global warming is a phenomenon that has been extensively studied in the scientific community. Indeed, the literature agrees on its significant impacts on our planet and its ecosystems (Trenberth et al., 2002; Shultz et al., 2014; Su et al., 2020; Qin et al., 2023b,a). According to National Aeronautics and Space Administration (NASA), the Earth's average surface temperature has increased by approximately 1.1°C since the late 19th century, with a warming trend since the 1970s. The primary cause of this warming trend is the increased Greenhouse Gas emissions, which have risen by more than 45% from the Industrial Revolution due to the burning of fossil fuels. The concentration of carbon dioxide in the atmosphere reached its maximum value in 2021.

The World Meteorological Organization (WMO) reports that the 10 warmest years on record have all occurred since 2005. In particular, 2016 and 2020 were the warmest years. The increase in global temperatures has also resulted in a sea level rise of about 21 cm (melting glaciers) since 1880, with almost half of that rise occurring in the last 25 years. The Arctic sea ice extent has declined by an average of 12.8% per decade since satellite records began in 1979, which is attributed to natural climate variability and human-caused warming.

The Intergovernmental Panel on Climate Change (IPCC) reports that extreme weather events, such as heat waves, droughts, and heavy precipitation, have become more frequent and intense in many regions of the world in recent decades, increasing the average temperature and the phenomena associated with climate change, as demonstrated by the growing climate anomalies reported in Figure 3.1. The available scientific research and data on global warming provide ample evidence of the reality of this phenomenon and its significant impact on the planet (see, for instance, Cavicchioli et al., 2019; Habibullah et al., 2022; Kemp et al., 2022).

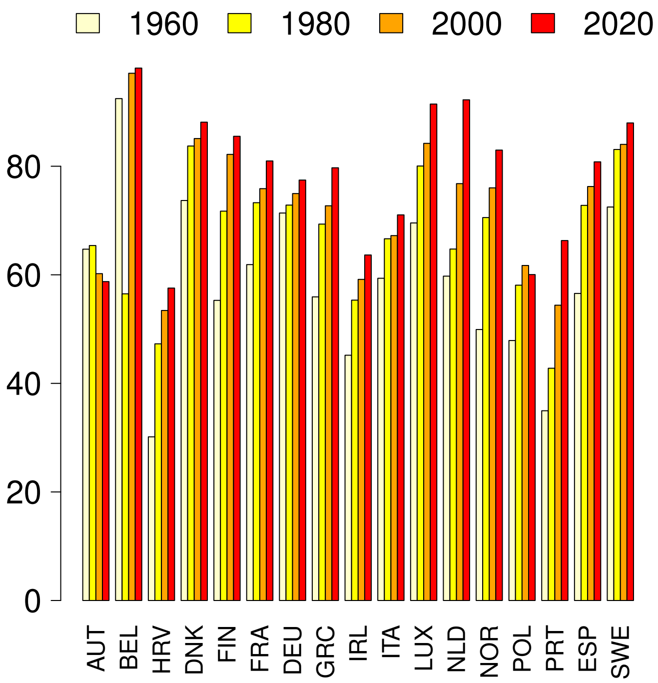
According to Nelson and Palmer (2007), Nelson et al. (2009) and Wang and Li (2020), urbanization is one of the main problems of climate change and global warming since it increases pollutant emissions. Figure 3.2 shows the percentage of Urban Population in a panel of selected European Countries. With the only exception of Austria, the percentage of urban population increased significantly from 1960 to 2020 in the eurozone.

Given such trend in the Urban Population growth, the average European pollution increased. As reported in Figure 3.3, the average share of temperature produced using GreenHouse Gas (GHG) emissions increased, except for the share of Methane (CH4).



Source: National Aeronautics and Space Administration (NASA), Goddard Institute for Space Studies (GISS)

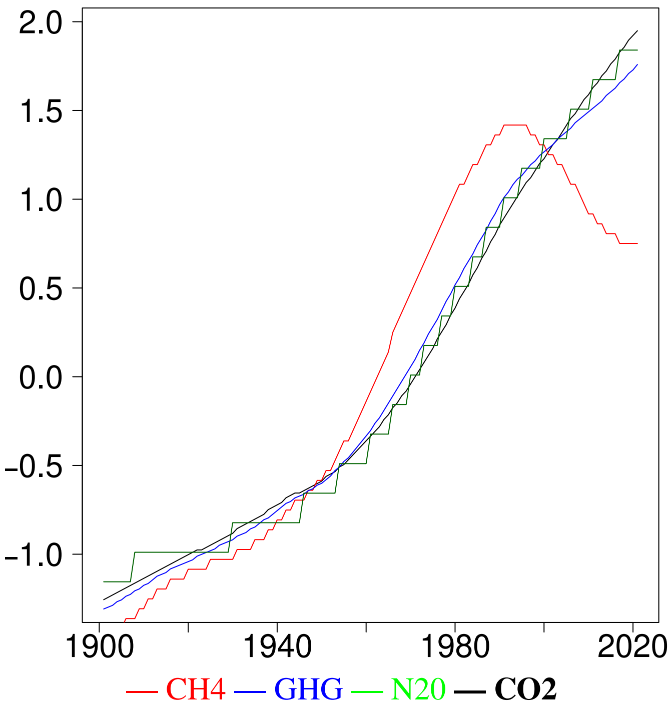
Figure 3.1: Combined land-surface air and sea-surface water temperature anomaly



Source: World Data Bank

Figure 3.2: Urban population as a percentage of total population

The other sources, such as Carbon Dioxide (CO2) and Nitrous Oxide (N20), exhibit a growing trend. Therefore, the increase in these elements leads to an increase in global warming, causing an ever-increasing increase in adverse climatic phenomena.



Source: Jones et al. (2023)

Figure 3.3: Share of temperature change from GreenHouse-Gas(GHG) emissions sources for the Eurozone

Given these premises, the climate change issue has been influencing the current state of the European economy. According to Bilgen (2014) and Martins et al. (2019), a natural dependency between global warming and gas demand exists. The gas price boomed due to the Russia-Ukraine war. Since we observed a relative drop in gas demand, we aim to identify whether this fall is ascribable only to the gas price increase or is a global warming consequence. In addition, due to the unstable financial and macroeconomic situation, we intend to estimate the role of Title Transfer Facility (TTF) price,[1] geopolitical risk, and temperature, in the current inflation rise to understand their contribution. To be more specific, the research questions are the following

[1]The TTF is a natural gas trading hub located in the Netherlands. It serves as a benchmark for natural gas prices in Europe.

H1: Does the rising temperature influence (more than the increase in TTF price) the decline in natural gas demand?

H2: Does the temperature and geopolitical risk contribute to the current European inflation surge?

To answer the first research question, we investigate the impact of exogenous shocks on gas demand in the Euro area using a Time-Varying Parameter Vector Autoregression (TVP-VAR) model. Given the dynamic nature of this model, it is particularly suitable for studying the effects of certain events. In particular, we focus on the effects of two events that occurred in recent years: the Covid-19 pandemic and the escalation of the Russia-Ukraine conflict. The second research question is addressed through the Wavelet technique, which allows us to identify short and long-term correlation frequencies, thus simultaneously allowing for the investigation of the lead-lag relationship.

Using monthly data from January 2015 to September 2023, we show the relevant role of average temperature in European gas demand contraction, independently from the time shock considered. Furthermore, we confirm the rush to store natural gas following the rifts between Russia and Ukraine, reporting increased demand for gas despite an increase in the TTF price. We find the presence of multiple breaks in the global interconnectedness of the system. To conclude, we assert the mitigating role of temperature in the current inflation surge.

The rest of the chapter is organized as follows. Section 3.2 presents a comprehensive literature review. Section 3.3 and 3.4 provide details on the data sources and methodologies employed. Section 3.5 analyzes and discusses the results, while section 3.6 concludes and provides some policy implications.

3.2 Literature Review

Over the years, many studies reviewed the factors of natural gas and energy demand (see, among others, Mu et al., 2018; Bastianin et al., 2019; Zheng et al., 2021; Lawal et al., 2022). Given the different nature of the elements affecting natural gas demand, we aim to disentangle its most significant determinants and explore the dynamic relationship with the recent inflation boom.

The literature investigate the impact of extreme events on the energy sector, which are becoming more frequent due to climate change (Qin et al., 2023a; Su et al., 2020). As natural gas is a crucial source of heating energy for Europe, numerous studies examine the relationship between energy sources and climate events. For instance, Qin et al. (2023b) investigate the relationship between extreme events, geopolitical turmoil, and supply chain stability, which strongly relies on the energy sector. According to Qui et al. (2020), which applies a wavelet-based causality analysis, the Oceanic Niño Index (ONI) index for climate change measurement has a negative influence on oil price and demand in the long run.[2] This result produce several relevant consequences since it emphasizes the rise in global temperature, which means a warmer winter, supporting the existing literature (Trenberth et al., 2002; Shultz et al., 2014). Additionally, recent investigations from Song et al. (2022b) claim the importance of extreme events in natural gas demand forecasting as a functional factor for the energy transition.

Moreover, the natural gas market is subject to periods of growth and decline due to the different economic conditions (Erias and Iglesias, 2022). The Covid-19 pandemic contributed to the contraction of natural gas demand. However, the subsequent period of post-pandemic recovery attracted inflationary pressures, especially in the European countries with the highest reliance on external sources for natural gas supply (Ruble, 2017; Pedersen et al., 2022). The BP Statistical Review of World Energy (June 2022) indicates that natural gas consumption accounts for almost a quarter of Europe's primary energy consumption. Given this high dependency, several scholars examined the economic impact of rising geopolitical events on natural gas supply in the Eurozone. Studies by Salameh and Chedid (2020), Lambert et al. (2022), and Gong and Xu (2022) highlight the importance of such events, emphasizing that EU sanctions on Russia's economy, for example, can negatively impact natural gas exports to Europe. This result is in line with Qureshi et al. (2022). Consequently, our study acknowledges the importance of considering geopolitical events in the EU context when forecasting

[2]The ONI is the rolling 3-month average temperature anomaly, a difference from the average, in the surface waters of the east-central tropical Pacific, near the International Dateline.

natural gas demand.

Gas demand factors in different economic regions

Broadly, the body of literature concerning the determinants of natural gas demand is extensive, encompassing a wide array of research. Notably, there is a prominent focus on China, where economic growth stands out as the foremost driver behind the expansion of natural gas demand. Concurrently, Mu et al. (2018) observe that the technological advancements exert a negative influence on consumption patterns. Liang et al. (2019) apply a Markov-Switching (MS) model to identify the different requirements of natural gas demand. They find “rapid” and “slow” growth regimes in the development process of natural gas consumption in China depending on different aspects such as natural gas price, industrialization level, and wealth. Wang and Li (2020) conclude that energy consumption structure, GDP, and urbanization rate are the three main influencing factors of natural gas demand. The role of industrialization and wealth in influencing the Chinese natural gas demand is confirmed by a wide range of scholars (see, for instance, Li et al., 2020; Zheng et al., 2021; Duan et al., 2021). In addition, the role of alternative energy prices is crucial to reduce the natural gas demand in China, as Wang and Lin (2014), Liang et al. (2019), and Li et al. (2022b) report.

Furthermore, given its prominent role in the global energy system, the United States natural gas market has also been extensively researched. Goldstein and Mohnen (1992) develop the milestone work of natural gas demand forecast in the context of growing climate uncertainty and global warming. Kelley (2017) claim the role of fossil fuel consumption and emissions as one of the reasons for climatic changes and natural disasters in the USA. Accordingly, different works try to estimate the negative impact of natural gas consumption and its main influencing factors. Indeed, Singh et al. (2023) state how the increasing population wealth could reduce natural gas consumption and simultaneously promote the development of alternative (and cleaner) production ways. In terms of factors that influence the natural gas demand, Gautam and Paudel (2018) and Adebayo et al. (2023), report the important role of temperature and global warming, emphasizing the influence of alternative energies in the natural gas demand mitigation. Other works studied the natural gas market in the US context (see, for instance, Zhang et al., 2018; Tiwari et al., 2019; Sharma and Escobari, 2018; Lawal et al., 2022). Tiwari et al. (2019) find a pro-cyclical behavior in the natural gas market similar to crude oil. Sharma and Escobari (2018) conclude about the significant role of market bubbles in energy pricing, especially natural gas and crude oil. Lawal et al. (2022) confirm this finding suggesting that disruptions in the market will be short-lived as the market will fundamentally adjust back to equilibrium.

Erdogdu (2010), Özmen et al. (2018), and Yukseltan et al. (2021), conduct different analyses to understand the natural gas market behavior in Turkey. Erdogdu (2010) reveals that natural gas demand elasticities in Turkey are quite low, meaning that consumers do not respond to possible abusive price increases by decreasing their demand or substituting natural gas with other energy sources. However, the substitution with other energy sources is found by İpek and İpek (2022). Özcan et al. (2013) report the important role of wealth and age in energy choices. Özmen et al. (2018) use predictive models MARS (Multivariate Adaptive Regression Splines) and CMARS (Conic Multivariate Adaptive Regression Splines) to forecast the one-day ahead natural gas demand of residential users. Including the temperature significantly improves the forecasting performance, confirming that the temperature is a relevant factor in predicting natural gas demand.

In contrast, natural gas dynamics in European countries received relatively little attention in the literature. However, this trend is changing due to the recent escalation of energy inflation following the Russia-Ukraine war. As a result, there is an increasing need for research to examine the factors that influence natural gas demand in Europe to understand how market forces impact energy prices in the region.

Over the last decade, investigations aimed at predicting natural gas consumption within European countries have predominantly centered on specific geographical areas, often neglecting to consider the broader context of Europe as a cohesive entity (Li et al., 2022c). The EU represents a coalition of European countries that share economic and political ties, approaching climate change issues in a coordinated way, as evidenced by its climate and energy targets. Although EU member states may establish their own climate and energy targets, these objectives are aligned with the European unified strategy. Consequently, it is important to clarify the prospects of natural gas in each EU member state. This observation is particularly critical because the literature show that natural gas markets have converged (Bastianin et al., 2019).

In their study, Dilaver et al. (2014) use a structural time series model to determine income and natural gas prices as significant factors for natural gas demand in OECD European countries. However, this analysis only employed annual data from 2012 to 2020, not considering the post-Covid period. Szoplik (2015) find that weather (temperature) has a pronounced effect on the natural gas market. Recent research by Su et al. (2023) highlight the importance of considering exogenous factors, such as geopolitical and climate factors. They suggest that transitioning towards greener technologies and supplies could have a positive impact on natural gas demand. In addition, their study focused on identifying bubbles in the current framework of growing global uncertainty, which is an important aspect to consider when forecasting natural gas demand in the region.

3.3 Data

We use two datasets to address the research questions introduced at page 124. First, we provide an exposition of the dataset employed for discerning the factors impacting natural gas demand. Then, we delve into an extensive examination of the different categories of inflation with the additional consideration of TTF price, geopolitical risk, and temperature.

Dataset: natural gas demand factors

In this section, we introduce the dataset we used to deal with the first research question developed at page 124. To ensure data availability, we use Euroarea monthly data from January 2014 to September 2023 ($T = 117$ months). First, we consider European natural gas demand and price, the latter proxied with the benchmark Title Transfer Facility (TTF) price. In addition, we use the average monthly Amsterdam temperature as a proxy of European temperature.[3]

[3] We compute several robustness checks with other measures. For instance, we consider the European average temperature and the temperature registered in the central part of Europe.

We employ the Geopolitical Risk (GPR) index developed by Caldara and Iacoviello (2022). However, since an aggregate European GPR is not available, we compute it as the simple average of the country-by-country Euroarea GPR indices. In addition, we consider the Industrial Production Index (IPI) to proxy the wealth in our analysis, given its relevance according to the whole literature and the unavailability of monthly data on European GDP. Finally, we also include the European Renewable Index (ERIX) to understand the role of renewable energy prices in gas demand. The entire list of variables and the relative sources can be found in Table 3.1.

Variable	Measure	Source
Gas Demand	Terajoules	Eurostat database
TTF price	Euro	Investing
Temperature	Celsius degree	NASA database
ERIX	Euro	Investing
GPR	Newspaper share	Iacovello webpage
IPI	Index 2015 = 100	Eurostat database

Note: In the NASA webpage that will open we fix the Lat/Lon of Amesterdam 52.3676° N, 4.9041° E, we choose daily data to compute the monthly average and we select "Temperature at 2 Meters".

Table 3.1: Variables measure and sources

Figure 3.14 and Table 3.7 (Appendix) show the original time series with the descriptive statistics and unit root tests. Accordingly, while gas demand and temperature exhibit a stationary behavior, they clearly show seasonality issues, and we correct them for seasonality. Except for GPR, we proceed with differentiating the series. In particular, while we apply a standard first difference on the Industrial Production Index, we consider the annual log difference of the financial values of TTF price and ERIX to obtain a sort of returns on annual basis. Figure 3.4 illustrates the final series used in this work. Table 3.2 reports the descriptive statistics and unit root tests, which confirm the stationarity of the entire set of endogenous variables.

As a preliminary analysis, Table 3.3 shows all the static correlations between variables. The correlation between temperature and gas demand in Europe is negative (-0.63). The reason is attributable to the role of natural gas in Europe: it is one of the primary energy sources used for residential and commercial heating. As temperatures decrease, the demand for heating increases, leading to a corresponding rise in natural gas consumption.

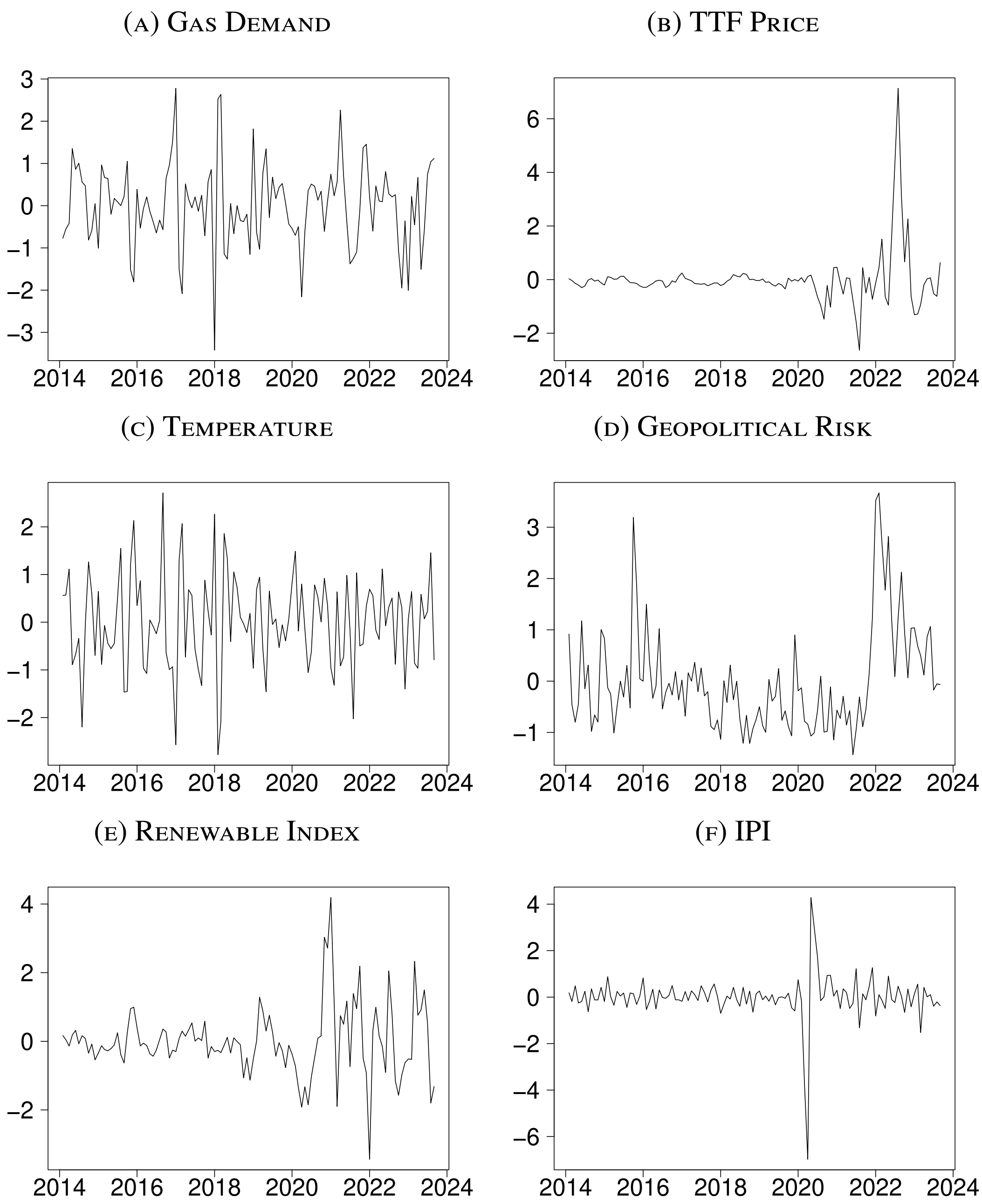


Figure 3.4: Differentiated series

Dataset: inflation, geopolitical risk and temperature

In this subsection, we describe the dataset that we consider to answer the second research question on page 124. Our objective is to examine the impact of gas price, temperature, and geopolitical risk on the real economy. In particular, we aim to investigate the influence of these variables on different inflation components. We consider the headline, core, and energy inflation categories. The former is ascribable to the price behavior of all goods in the Euro area. The core inflation is a proxy of the

	Demand	TTF	Temp	IPI	ERIX	GPR
Mean	-0.0000	0.0000	-0.0000	0.0000	-0.0000	-0.0000
Med	0.0924	-0.0728	-0.0068	0.0144	-0.0904	-0.2065
SD	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Max	2.7790	7.1337	2.7111	4.2864	4.1905	3.6686
Min	-3.4209	-2.6305	-2.7793	-6.9802	-3.4396	-1.4354
ADF	-5.9695 ***	-4.0295 ***	-7.6726 ***	-5.4832 ***	-4.8503 ***	-3.1513 ***
PP	-88.7175 ***	-42.3967 ***	-92.4347 ***	-82.2549 ***	-60.2107 ***	-46.3219 ***
KPSS	0.0306	0.1227	0.0251	0.0394	0.0465	0.3231

*p<0.1; **p<0.05; ***p<0.01

Note: The unit roots (the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS)) tests are conducted selecting the lag with the lowest AIC and with a constant specification of the deterministic component.

Table 3.2: Descriptive statistics and unit root tests of differentiated series.

	Demand	TTF	Temp	IPI	ERIX	
TTF	0.0579	-	-	-	-	-
Temperature	-0.6353	0.0393	-	-	-	-
IPI	0.1907	0.0122	-0.0360	-	-	-
ERIX	-0.0316	0.0476	-0.0138	0.0394	-	-
GPR	0.0267	0.1725	0.0024	-0.0258	-0.0848	-

Table 3.3: Static correlation matrix

overall inflation, encompassing various components, such as food and energy prices, which often exhibit higher volatility and are susceptible to inflationary spikes. Finally, energy inflation focuses on the contribution of energy commodities to price increases. All these data are based on the Harmonised Index of Consumer Prices (HICP) for the Euro area, and Table 3.4 reports the sources of each variable. The dataset spans from January 2014 to September 2023 ($T = 117$ months).

Variable	Measure	Source	Token
Headline Inflation	Index 2015 = 100	Eurostat database	[CP00]
Core Inflation	Index 2015 = 100	Eurostat database	[TOT_X_NRG_FOOD]
Energy Inflation	Index 2015 = 100	Eurostat database	[NRG_FOOD_S]

Table 3.4: Inflation components and sources

In Figure 3.5, we illustrate the behavior of the differentiated HICP for each category, headline, core and energy. We do not include TTF price, temperature, and geopolitical risk because the graphical representation is described in Figures 3.4(b), 3.4(c), and 3.4(d). Table 3.5 reports the descriptive statistics with the unit root tests. We can state that the differentiated inflation series are stationary at 5%. However, it is interesting to note that the latter part of the charts, after the Covid-19 period, exhibits a non-stationary behavior. This situation is due to the surge in the inflation levels caused by the recovery period after the Covid-19 pandemic and then with the Russia-Ukraine conflict.

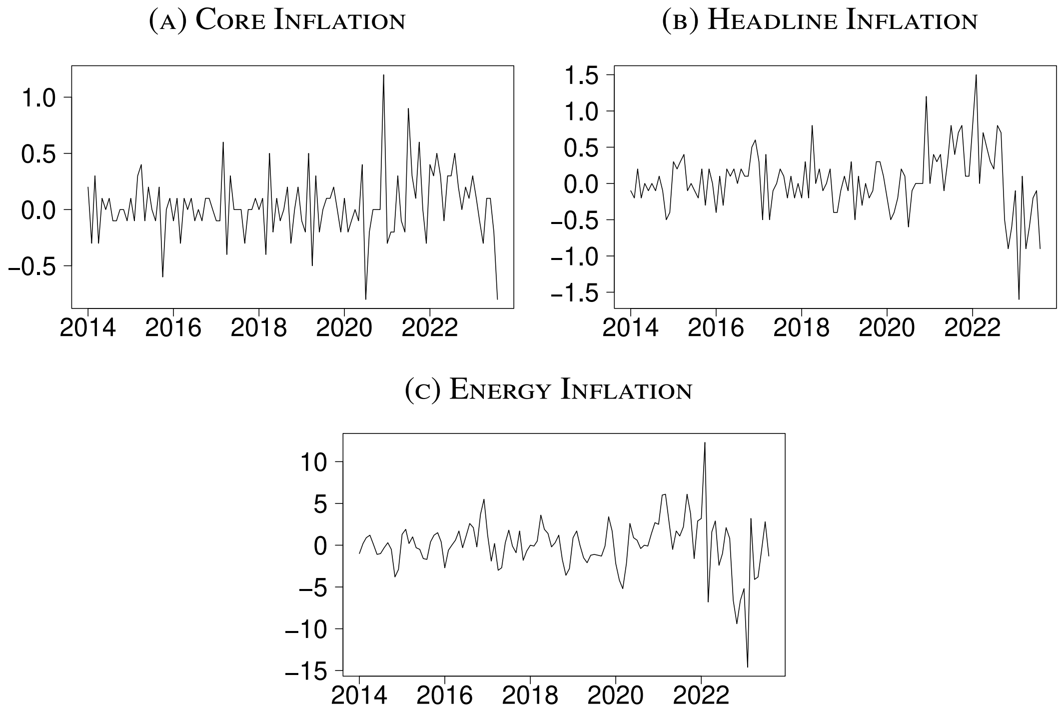


Figure 3.5: Differentiated CPI components

	Core	Headline	Energy
Mean	0.0319	0.0302	-0.0284
Med	0.0000	0.0000	0.0500
SD	0.2852	0.4239	3.1578
Max	1.2000	1.5000	12.3000
Min	-0.8000	-1.6000	-14.6000
ADF	-3.79824 ***	-2.8917 *	3.6551 **
PP	-144.5290 ***	-101.4506 ***	-86.4098 ***
KPSS	0.2712	0.1097	0.1099

*p<0.1; **p<0.05; ***p<0.01

Note: The unit roots (the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS)) tests are conducted selecting the lag with the lowest AIC and with a constant specification of the deterministic component.

Table 3.5: Descriptive statistics and unit root tests of inflation differentiated series.

From a static point of view (Table 3.6), the correlation between TTF price and inflation components is positive. Quite the opposite, the temperature is inversely correlated with all the inflation components. However, while GPR and headline/core inflation are positively correlated, the correlation between GPR and energy inflation is almost zero. Nevertheless, due to the static nature of the correlation data, we cannot understand the underlying dynamics driving these patterns. Since we are working with macroeconomic series, understanding the short, medium, or long dynamics is relevant. Consequently, we analyze the phase-plot relationship between inflation, TTF price, GPR, and temperature with a wavelet method.

	TTF	GPR	Temperature
Core	0.1149	0.1118	-0.0870
Headline	0.1826	0.1111	-0.1520
Energy	0.0838	0.0039	-0.1209

Table 3.6: Static correlation between inflation, TTF, GPR and temperature.

3.4 Methodology

In this work, we follow two different methodologies to fulfill the two research questions on page 124. To identify the main factors of natural gas demand, we apply a time varying VAR model for a twofold reason. First, it allows us to understand the different impacts of exogenous shocks (*i.e.* the Covid-19 pandemic and the Russia-Ukraine war). Second, the Generalized Forecast Error Variance Decomposition enables the discussion of the spillovers and the definition of pairwise relationships.[4] Besides, we apply a Wavelet-based study to understand the role of temperature in the context of rising inflation. Accordingly, we follow a dynamic in and out-of-phase analysis to understand the dynamic relationship between the variables.

Time-Varying Parameter VAR

The Time-Varying Parameter Vector AutoRegression (TVPVAR) model has gained notable importance as a prominent instrument to investigate the dynamics beyond the financial and macroeconomic time series. In contrast to the approach of Del Negro and Primiceri (2015), which employs Gibbs sampling and the Markov chain Monte

[4] As we noticed on page 10, the definition of spillover is not unanimous. In this case, we mean the spillover as a mechanism of influence from one variable to another.

Carlo (MCMC) technique to delineate time-varying parameters, our methodology adheres to the framework set by Koop and Korobilis (2013). We also follow the empirical applications of Antonakakis et al. (2020) and Foglia et al. (2023).This framework is rooted in Bayesian principles for parameter initialization, followed by the application of a recursive method to derive the time-varying coefficients.Koop and Korobilis (2013) include the parameter variation to avoid the definition of rolling window size, a requisite in conventional rolling dynamic analyses. This methodology exhibits sensitivity to outliers and offers an excellent way to examine the interconnected dynamics of data characterized by low frequencies.

Let the following companion form of the TVPVAR

$$\boldsymbol{y}_t = \boldsymbol{\vartheta}_t \boldsymbol{x}_{t-1} + \boldsymbol{\varepsilon}_t \quad \text{with} \quad \boldsymbol{\varepsilon}_t \sim N(0, \boldsymbol{\Omega}_t) \tag{3.1}$$

where

$$\underset{(n \times np)}{\boldsymbol{\vartheta}_t} = \begin{bmatrix} \boldsymbol{\vartheta}_{1t} & \boldsymbol{\vartheta}_{2t} & \dots & \boldsymbol{\vartheta}_{pt} \end{bmatrix} \quad \text{and} \quad \underset{(np \times 1)}{\boldsymbol{x}_{t-1}} = \begin{bmatrix} \boldsymbol{y}_{t-1} \\ \boldsymbol{y}_{t-2} \\ \vdots \\ \boldsymbol{y}_{t-p} \end{bmatrix}.$$

In Equation 3.1, $\boldsymbol{y}_t$ is the n-dimensional vector where each component is calculated as a deviation from the unconditional mean. The matrices $\boldsymbol{\vartheta}_{pt}$ are $n \times n$ matrices containing the time-varying model parameters, p is the number of lags, and $\boldsymbol{\varepsilon}_t$ is the vector of disturbances conditional to the information set $\mathcal{I}_{t-1}$. In particular, n is the number of the variables $n = 6$ and, according to the Bayesian, Akaike, and Hannan-Quinn ICs, the number of lags is $p = 1$.

To initialize parameters, we split our dataset of dimension T into two subsamples named training (T_0) and test (T_1) set. The first set estimates the initial matrix $\boldsymbol{\vartheta}_0$, and the second is employed to obtain the estimates of the time-varying parametric matrices $\boldsymbol{\vartheta}_t$ for $t = 1, 2, \dots, T_1$ recursively. T_0 is fixed from January 2014 to December 2018 ($T_0 = 60$) while the rest of the sample is updated recursively according to the methodology ($T_1 = 57$).[5]

[5] We select T_0 accounting for the "stable" per Covid-19 period. We did different trials around that date, and the results are robust.

Let $\boldsymbol{\Phi}_t = \mathrm{vec}(\boldsymbol{\vartheta}_t)$, we assume that each element is a random walk according to the equation

$$\boldsymbol{\Phi}_t = \boldsymbol{\Phi}_{t-1} + \boldsymbol{\nu}_t \quad \text{with} \quad \boldsymbol{\nu}_t \sim N(\mathbf{0}, \boldsymbol{\Sigma}_t), \tag{3.2}$$

where $\boldsymbol{\nu}_t$ is a $n^2p \times 1$ vector.

The Kalman filter initialization is obtained from the VAR(p) estimation in the training set, according to prior techniques developed by Primiceri (2005) and Del Negro and Primiceri (2015), who set the prior

$$\boldsymbol{\Phi}_0 \sim N(\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0), \tag{3.3}$$

where $\boldsymbol{\Phi}_0 = \mathrm{vec}(\boldsymbol{\vartheta}_0)$ and $\boldsymbol{\vartheta}_0$ is the estimated matrix of parameters, and the initial residual covariance matrix is $\boldsymbol{\Omega}_0 = T_0^{-1}\boldsymbol{E}_0'\boldsymbol{E}_0$ where $\boldsymbol{E}_0$ is a $T_0 \times n$ matrix. To initialized the multivariate Kalman filter, we need to set the following initial conditions

$$\begin{cases} \boldsymbol{\vartheta}_t|\boldsymbol{\mathcal{I}}_{t-1} = \boldsymbol{\vartheta}_{t-1}, \\ \boldsymbol{\varepsilon}_t|\boldsymbol{\mathcal{I}}_{t-1} = \boldsymbol{y}_t - \boldsymbol{\vartheta}_{t-1}\boldsymbol{x}_{t-1}, \\ \boldsymbol{\Omega}_t|\boldsymbol{\mathcal{I}}_{t-1} = \kappa_2\boldsymbol{\Omega}_{t-1} + (1-\kappa_2)\left.\dfrac{\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'}{T_0}\right|\boldsymbol{\mathcal{I}}_{t-1}, \\ \boldsymbol{\Sigma}_t^*|\boldsymbol{\mathcal{I}}_{t-1} = \kappa_1^{-1}\boldsymbol{\Sigma}_{t-1} = \kappa_1^{-t}\boldsymbol{\Sigma}_0. \end{cases} \tag{3.4}$$

When $t = 1$ the following starting condition hold:

$$\begin{cases} \boldsymbol{\vartheta}_1 = \boldsymbol{\vartheta}_0, \\ \boldsymbol{\Omega}_1 = T_0^{-1}\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'|\boldsymbol{\mathcal{I}}_{t-1} = \boldsymbol{\Omega}_0, \\ \boldsymbol{\Sigma}_1^* = \kappa_1^{-1}\boldsymbol{\Sigma}_0. \end{cases}$$

To guarantee numerical stability, Koop and Korobilis (2014) and Del Negro and Primiceri (2015), incorporate a couple of decay factors into the Kalman filter algorithm. Following Koop and Korobilis (2013), we set these parameters to $\kappa_1 = 0.99$ and

$\kappa_2 = 0.96$. Thus, the multivariate Kalman filter proceeds as follows:

$$\boldsymbol{\Omega}_t = z'_{t-1}(\boldsymbol{\Sigma}^*_t|\mathcal{I}_{t-1})z_{t-1} + \kappa_2\boldsymbol{\Omega}_{t-1} + (1-\kappa_2)\left.\frac{\varepsilon_t\varepsilon'_t}{T_{t-1}}\right|\mathcal{I}_{t-1}, \tag{3.5}$$

$$\boldsymbol{K}_t = (\boldsymbol{\Sigma}^*_t|\mathcal{I}_{t-1})z_{t-1}\boldsymbol{\Omega}^{-1}_t, \tag{3.6}$$

$$\boldsymbol{\Phi}_t = \boldsymbol{\Phi}_{t-1} + \boldsymbol{K}_t\varepsilon_t, \tag{3.7}$$

$$\varepsilon_t = \boldsymbol{y}_t - \boldsymbol{\vartheta}_t\boldsymbol{x}_{t-1}, \tag{3.8}$$

$$\boldsymbol{\Sigma}_t = (\boldsymbol{I}_{n^2p} - \boldsymbol{C}_t)\boldsymbol{\Sigma}^*_t|\mathcal{I}_{t-1}, \tag{3.9}$$

where $t = T_1 - T_0$, $\boldsymbol{C}_t = \boldsymbol{K}_t z'_{t-1}$, $z_{t-1} = \boldsymbol{x}_{t-1} \otimes \boldsymbol{I}_n$, $\boldsymbol{I}_n$ is the n-dimensional identity matrix. The Kalman gain $(\boldsymbol{K}_t)$ determines the degree of adjustment required for the time-varying parameter $\boldsymbol{\vartheta}_t$ in each state. When the eigenvalues of matrix $\boldsymbol{\Sigma}^*_t$ are low, the prior states should closely resemble the parameters $\boldsymbol{\vartheta}_t$, the eigenvalues of the error variance $\boldsymbol{\Sigma}_t$ are low, and the parameter matrix $\boldsymbol{\Omega}_t$ should be similar to that provided by the prior.[6]

The dynamic nature of the model allows the estimation of Time-Varying Impulse Response Functions (IRFs), which we define to understand the role of exogenous shocks in the system. We follow the Generalized version proposed in Koop et al. (1996) and Pesaran and Shin (1998) to avoid identification issues. Given the stationarity of the variable, the Wold representation theorem allows us to retrieve the Time-Varying Parameters Moving Average (TVPMA). The TVPVMA representation is obtained by recursive substitution

$$\boldsymbol{y}_t = \boldsymbol{M}'(\boldsymbol{V}^{k-1}_t\boldsymbol{x}_{t-k-1} + \sum_{i=0}^{k}\boldsymbol{V}^i_t\boldsymbol{\xi}_{t-i}), \tag{3.10}$$

where

$$\underset{(np\times n)}{\boldsymbol{M}} = \begin{bmatrix}\boldsymbol{I}_n\\ \boldsymbol{0}\\ \vdots\\ \boldsymbol{0}\end{bmatrix}, \underset{(np\times np)}{\boldsymbol{V}_t} = \begin{bmatrix}\boldsymbol{\vartheta}_t\\ \boldsymbol{I}_{n(p-1)}\boldsymbol{0}_{n(p-1)\times n}\end{bmatrix}, \underset{(np\times 1)}{\boldsymbol{\xi}_t} = \boldsymbol{M}\varepsilon_t.$$

[6]This methodology is available in MatLab and R. We develop a Gretl main source code available in Appendix 3.B.

Considering the limit as k approaches ∞, we obtain

$$\boldsymbol{y}_t = \sum_{i=0}^{\infty} \boldsymbol{M}'\boldsymbol{V}_t^i \boldsymbol{\xi}_{t-i}, \tag{3.11}$$

that, considering $\gamma_{it} = \boldsymbol{M}'\boldsymbol{V}_t^i \boldsymbol{M}$ can be transformed as follows:

$$\boldsymbol{y}_t = \sum_{i=0}^{\infty} \gamma_{it} \varepsilon_{t-i} \tag{3.12}$$

The Generalized Impulse Response Functions (GIRFs), represented as ϱ, illustrate the reactions of all variables j to an exogenous shock from variable i. Given the absence of a structural model, we compare scenarios where variable i is shocked with the case that the variable i remains unaffected. According to Antonakakis et al. (2020), this difference can be attributed to the shock in variable i

$$\varrho_t(H, \boldsymbol{\lambda}_{jt}) = E(\boldsymbol{y}_{t+H} | \boldsymbol{\epsilon}_j = \boldsymbol{\lambda}_{jt}) - E(\boldsymbol{y}_{t+j} | \boldsymbol{\mathcal{I}}_{t-1}) = \frac{\gamma_{Ht} \boldsymbol{\Omega}_t \boldsymbol{\epsilon}_j}{\boldsymbol{\lambda}_{jt}} \tag{3.13}$$

where, γ is the coefficient matrix from the TVPMA representation, $\boldsymbol{\lambda}$ is the standard deviation of the error term for the j-th equation, $\boldsymbol{\epsilon}_j$ is an $n \times 1$ selection vector with unity in the j-th position, and zero otherwise.

Spillover analysis based on TVP-VAR

The estimation of time-varying coefficients finds practical utility in the measure of the generalized connectedness procedure, as initially introduced by Diebold and Yilmaz (2012); Diebold and Yılmaz (2014). This procedural approach is rooted in the underpinning structure of Generalized Impulse Response Functions (GIRFs), as delineated in (3.13). In this case, we use the initialization of (3.4) up until $T_0 = 72$, and then we estimate the TVPVAR model on the whole dataset $T_1 = T$. In this way, we are able to identify spillovers for the entire length of the sample in order to conclude about potential breaks in the system interconnectedness.

We want to identify the Total Connectedness Index (TCI) introduced in Chapter 1 to understand the interconnectedness between the variables. Accordingly, we define the Generalized Forecast Error Variance Decomposition (GFEVD, $\boldsymbol{\theta}$). The GFEVD represents the pairwise directional connectedness from j to i. It is computed as follows

$$\boldsymbol{\theta}_{ij,t}(H) = \frac{\sum\limits_{h=1}^{H-1} \varrho_{ij,t}^2}{\sum\limits_{j=1}^{n}\sum\limits_{h=1}^{H-1} \varrho_{ij,t}^2}. \tag{3.14}$$

The GFEVD are normalized so that each row sums up to 1, meaning all the variables together explain 100% of variable i's forecast error variance. The denominator in Equation 3.14 is the cumulative effect of all the shocks, while the numerator represents the cumulative effect of a shock in variable i. Therefore, according to Chatziantoniou et al. (2021), we are able to construct the unbiased TCI

$$TCI = \frac{1}{n-1}\sum_{i,j=1}^{n} \boldsymbol{\theta}_{ij,t}(H) \quad \forall i \neq j \tag{3.15}$$

Wavelet Analysis

Wavelet analysis is a mathematical technique to analyze signals and data in both time and frequency domains. It involves breaking down a signal into different frequency components using wavelets, which are small, wave-like functions. The wavelet technique is excellent for estimating co-movement and causation between two-time series. A wavelet is a real-valued square-integrable function defined as

$$\Psi_{\nu,s}(t) = \frac{1}{\sqrt{b}}\Psi\left(\frac{t-\nu}{b}\right), \quad \Psi(.) \in \mathbf{L}^2, \quad s \neq 0, \tag{3.16}$$

where $\mathbf{L}^2$ is the Hilbert space of square-integrable one-dimensional functions, and the scalar $1/\sqrt{b}$ denotes a normalization factor ensuring unit wavelet variance and a comparable value across b, the scale, and ν, the location parameters.

The most popular mother wavelet is the Morlet wavelet empirically introduced by Morlet et al. (1982) and Goupillaud et al. (1984)

$$\Psi_M(t) = \pi^{-1/4}\exp\left\{i\omega_0 t - \frac{t^2}{2}\right\}, \tag{3.17}$$

where $\pi^{1/4}$ ensure the wavelet integrability through the Hilbert space, and ω_0 denotes the central frequency of the wavelet set as 6 as the majority of economic applications (see, for instance, Aguiar-Conraria et al., 2008; Vacha and Barunik, 2012; Yang et al., 2016; Ahmed, 2022). Accordingly, Soares et al. (2011) claim that $\omega_0 = 6$ is used since it presents the most desirable compromise between frequency and time localization. This wavelet is classified as complex, thus with both real and imaginary parts, which allows the identification of amplitude and phase.

According to Vacha and Barunik (2012), the Continuous Wavelet Transform (CWT) of a time series that belongs to the Hilber space, is defined as

$$\mathbf{W}_x(\nu,b) = \int_{-\infty}^{\infty} x_t \frac{1}{\sqrt{|b|}} \Psi^c\left(\frac{t-\nu}{b}\right) dt, \tag{3.18}$$

where "^{c}" indicates the complex conjugate operator and x_t is the time series. According to Grinsted et al. (2004), we obtain x_t, inverting the CWT function, integrating the Hilbert space integral by the location parameter and the positive part with respect to the scale parameter b

$$x_t = \frac{1}{C_\Psi} \int_0^{\infty} \left[\int_{-\infty}^{\infty} \mathbf{W}_x(\nu,b) \Psi^c\left(\frac{t-\nu}{b}\right) d\nu\right] \frac{db}{b^2} \tag{3.19}$$

where C_Ψ is the local continuous phase projection of the time series x(t) on the Morlet transformation. The variance is

$$\sigma_x^2 = \frac{1}{C_\Psi} \int_0^{\infty} \left[\int_{-\infty}^{\infty} |\mathbf{W}_x(\nu,b)|^2 d\nu\right] \frac{db}{b^2} \tag{3.20}$$

where $|\mathbf{W}_x(\nu,b)|^2$ is the local wavelet power spectrum (sometimes called scalogram or wavelet periodogram) used to interpret the degree of the local variance x_t on a scale-by-scale basis. The wavelet power spectrum reflects the intensity of the time series variance for each time and frequency.

Further, we employed the cross-wavelet transformation (XWT) to investigate the interdependence between two individual time series x_t and y_t. It can be defined as follows

$$\mathbf{W}_{x,y}(\nu,b) = \mathbf{W}_x(\nu,b)\mathbf{W}_y^c(\nu,b) \tag{3.21}$$

where W_y^c is the complex conjugate of the y_t CWT. From the XWT, we can define the cross-wavelet power (XWP) as its absolute value. The XWP indicates the power similarity between the two time series. In addition, the series co-movement over time and across frequencies can be identified by applying wavelet coherence charts, as introduced in Torrence and Compo (1998) and Torrence and Webster (1999)

$$R^2_{x,y}(\nu, b) = \frac{\left| S\left(\mathbf{W}_{x,y}(\nu, b)\right)\right|^2}{S\left(|\mathbf{W}_x(\nu, b)|^2\right) S\left(|\mathbf{W}_y(\nu, b)|^2\right)} \tag{3.22}$$

where S is a smoothing operator in both time and scale, which leads to the coherence $R^2_{x,y} \in [0, 1]$. Therefore, we can identify the intensity of co-movement between series. When the $R^2_{x,y}$ is around one, the intensity is quite relevant, and vice versa in 0. Despite this feature, we cannot distinguish between positive and negative effects. Consequently, Torrence and Webster (1999) introduced the phase plot to limit and overcome this issue. The wavelet coherence phase difference is determined as the angle of the complex coherency

$$\zeta_{x,y} = \arctan^{-1}\left(\frac{\mathcal{I}\{S(\mathbf{W}_{x,y}(\nu, b))\}}{\mathcal{R}\{S(\mathbf{W}_{x,y}(\nu, b))\}}\right), \tag{3.23}$$

where $\mathcal{I}$ and $\mathcal{R}$ are the imaginary and real part operators. The phase element $\zeta_{x,y}$ is defined between $|\pi|$, capturing the lead-lag (causal) relationship between x_t and y_t at each time and frequency. A zero phase difference indicates that the two series move together, while extreme values of π show an opposite direction. For this reason, wavelet analysis is becoming relevant in finance to identify possible hedging operations, as reported by Gallegati and Semmler (2014) and Addison (2017). Generally, the phase plot is reported in the cross-wavelet chart with arrows. Depending on the pointed direction, we retrieve information about the series co-movement. If the arrow points up (down), the first (second) series is leading the second (first), and the wavelet coherence phase is $\zeta_{x,y} =\in [0, \pi/2]$ $([-\pi/2, 0])$. Quite the opposite, if the arrow points right (left), the two series move in phase (out-of-phase), as a result of the wavelet coherence phase $\zeta_{x,y} =\in [\pi/2, \pi]$ $([\pi, -\pi/2])$. In this case, the first series predicts the second (and vice versa).

Most of the economics and financial applications focused on the study of the standard XWT and phase diagram. In our case, we compute additional wavelets differentiating for a third z_t time series. Therefore, to identify the dynamic correlation between two-time series x_t and y_t, we eliminate the influence of the controlling variable z_t. Economically, the intuition of this approach involves first conducting a regression of y_t on z_t. Subsequently, the wavelet analysis is applied to the error time series of the preliminary regression and another variable x_t.

According to Kendall et al. (1979) and Aguiar-Conraria and Soares (2014), the partial wavelet coherence is given by

$$R^2_{x,y|z}(\nu, b) = \frac{|R_{x,y}(\nu, b) - R_{x,z}(\nu, b) R^c_{y,z}(\nu, b)|^2}{|1 - R_{x,y}(\nu, b)^2||1 - R_{y,z}(\nu, b)^2|} \tag{3.24}$$

where $R_{x,z}(\nu, b)$ is the wavelet coherence between x_t and z_t, $R_{x,y}(\nu, b)$ is the wavelet coherence between x_t and y_t, and $R_{y,z}(\nu, b)$ is the wavelet coherence between y_t and z_t. Then, we define the partial phase-delay (phase-difference) of x_t over y_t, given the z_t series, as the angle of $R^2_{x,y|z}(\nu, b)$

$$\zeta_{x,y|z} = \arctan^{-1}\left(\frac{\mathcal{I}\{R^2_{x,y|z}(\nu, b)\}}{\mathcal{R}\{R^2_{x,y|z}(\nu, b)\}}\right). \tag{3.25}$$

For each wavelet coherence plot, we report with a dotted white line the so-called Cone Of Influence (COI), a threshold below which regions of the wavelet spectrum are subject to edge effects.[7]. However, according to Percival and Walden (2000), these edge effects are likely to downward bias the results.

3.5 Results

Esmaeili and Rafei (2021) demonstrate the importance of the TVPVAR to capture inherent dynamics in the gas demand forecast. Accordingly, it allows to capture seasonality, short-term fluctuations, and long-term trends in the data. As we saw in Section 3.2, following Mezghani and Haddad (2017), and Qiao et al. (2023), the energy

[7]These emerge when the CWT has border distortions at the beginning and the end of the power spectrum.

demand is influenced by a range of factors, including weather patterns, geopolitical events, technological advancements, and policy changes. These factors are not constant over time, thus some structural breaks in their relationships could arise (as reported by Dogan, 2016; Pata and Caglar, 2021).

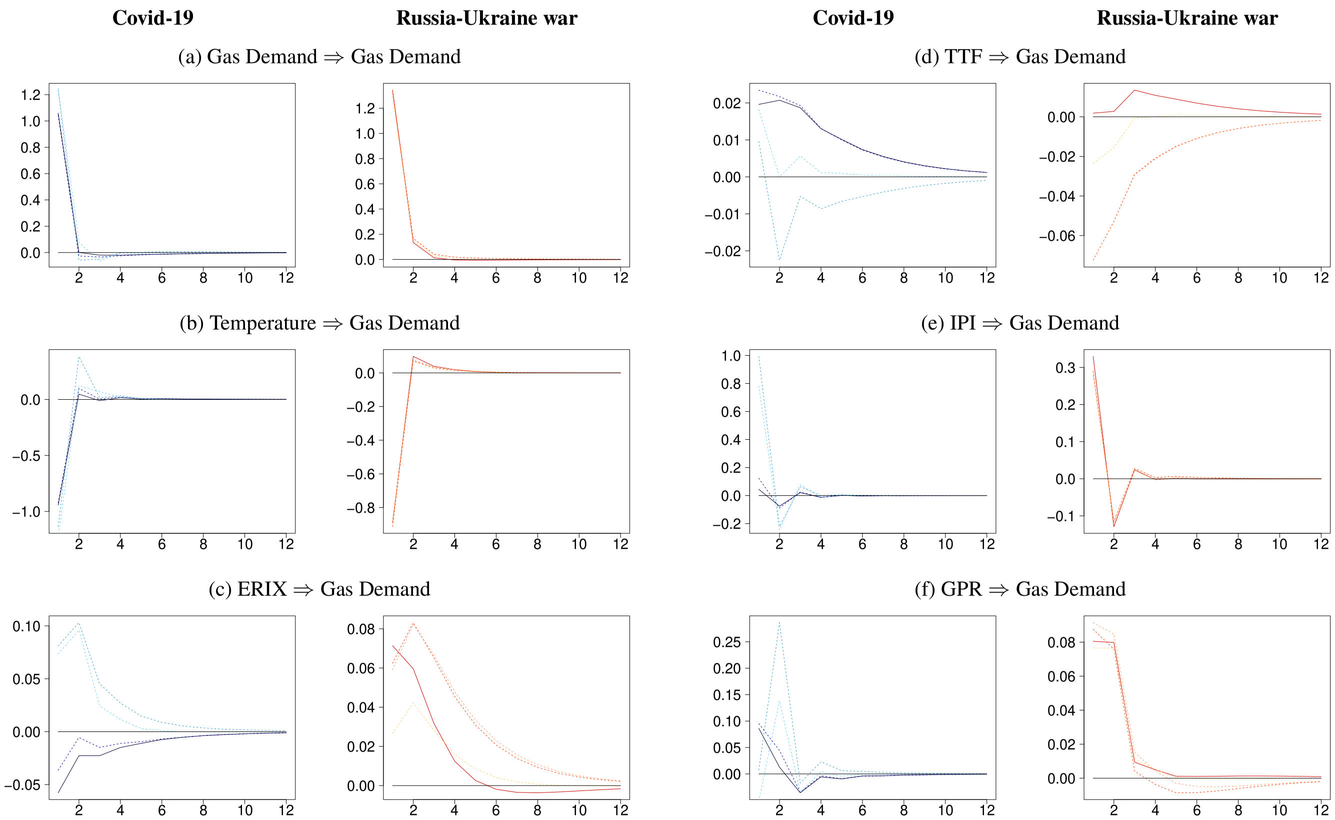
3.5.1 Generalized Impulse Response Functions (GIRFs)

Figure 3.6 reports the Generalized Impulse Response Functions (GIRFs) for 13 months. Since we use a time varying model, we compute the natural gas demand on two exogenous shocks: the Covid-19 pandemic (March 2020) and the Russia-Ukraine war (February 2022). We also report with dotted and warmer lines the GIRFs of three months after the main shock period to discuss the role of the time-varying coefficient. Given the stationarity of the data, each shock is quickly reabsorbed by the system.

Since we standardize variables, we make shocks comparable in magnitude. The reaction of gas demand to exogenous TTF price shock differs between the Covid-19 pandemic and the Russia-Ukraine war. Both shocks share a contained effect on gas demand. According to Gros (2023), the relatively low reaction of gas demand to TTF price is due to the apparent higher elasticity of demand in those major EU gas markets where prices were allowed to increase much higher than anticipated.

The Russia-Ukraine conflict had a louder impact on natural gas demand since it directly affected European energy security. This conflict led to a limitation of Russian gas supplies in mid-2022. Consequently, after the initial panic spread, Euro-area countries reduced their gas consumption. However, they pass through a noteworthy sudden increase in gas demand to ensure sufficient stock of gas given the conflict (Obadi and Korcek, 2020). As a result, despite an increase in TTF price, the corresponding natural gas demand increases due to the need for security of supply (confirming the thesis in Tesio et al., 2022). After the first month of gas storage, increases in TTF price lead to a decrease in gas demand.

During the Covid-19 pandemic, the rigidity of gas demand due to lockdown and restriction periods can explain the positive reaction of TTF shocks. Given that the



Note: The darker colour shows GIRFs corresponding to the shock period, the other lighter colours represent the shocks set in the 3 subsequent periods. We do not report confidence band here, but they are available upon request. On average, the GIRFs are singificant up until the 2-nd month.

Figure 3.6: Time-Varying GIRFs

consumption of natural gas (and more generally of energy) was almost constant during the pandemic,[8] the price shocks did not produce a significant effect on the quantity demanded. Furthermore, during the pandemic recovery, the industrial sector tried to replace productive energy sources as it is heavily dependent on fossil sources, such as natural gas. As a result, we started to have a negative effect of TTF price on Euroarea gas demand that simultaneously increased with the bettering performances of the renewable energy sector (ERIX).

As expected, the GIRFs indicate that an increase in the average temperature is associated with an immediate decline in gas demand during both the Covid-19 pandemic and the Ukraine war. On average, the temperature shock produces more pronounced effects on gas demand than the TTF price shock. The immediate increase in temperature led to a reduction in gas demand of approximately 1 point in both situations. In the short term, we observed a greater temperature shock at the beginning of 2020. However, in the medium term, the temperature shock has a more persistent effect during the Russia-Ukraine conflict with respect to the Covid-19 pandemic. In addition, the temperature is the main factor driving natural gas demand, as demonstrated by the values of the variance decomposition in Figure 3.7.

During the Russia-Ukraine conflict, the persistent effect of the temperature shock could be due to various factors. First, the war may have disrupted gas supply routes or led to concerns about energy security, which could have influenced medium-term gas demand patterns. On the other hand, the Covid-19 pandemic caused immediate widespread economic disruptions and lockdown measures, resulting in reduced economic activity and energy demand. In particular, the quicker absorption of the temperature shock during the Covid-19 period depends on the warmer seasons (from April onwards) in which the lockdowns and restrictions occurred.[9]

In Figure 3.4 (a), we observed a sharp decline in the Industrial Production Index following the outbreak of the Covid-19 pandemic. Consistently, we expected shocks during the beginning of 2020 to have a more pronounced effect on gas demand than

[8]The implementation of measures relating to remote working and the development of the main activities directly from home increase the dependency on the energy sector.

[9]We tested the effects of temperature shocks in different months, finding a strong influence on the season where they occur. Specifically, we conducted several trials during the warmer season and found that the effects of the shock were significantly lower.

those during the Ukrainian war. This hypothesis is supported by the relative GIRFs, which indicate an immediate positive response in the Gas Demand series following a sudden exogenous increase in the IPI during the Covid-19 crisis. However, during the recent conflict, this reaction did not occur. In particular, after an immediate effect of 0.3 points on natural gas demand, the GIRF declined and stabilized around zero. These outcomes suggest that IPI influences the natural gas demand in the short run and should be considered by investors and policymakers in energy demand forecasting and energy security planning disclosure.

The European Renewable Index (ERIX) shock prompts different reactions in natural gas demand: when the shock comes from the Covid-19 pandemic, an immediate negative effect of 0.05 occurs; conversely, during the Russia-Ukraine conflict, it yields a more substantial positive impact of 0.07. As expected, the significance of the ERIX shock amid the Covid-19 pandemic was limited due to the rigidity of economic agents from the energy sector, which reduced after the recovery period. Quite the opposite, the ERIX shock produced a pronounced and positive effect on natural gas demand during the Russia-Ukraine war, particularly in the short term. At the beginning of 2022, the renewable energy market experienced a marginal contraction, coinciding with a reduction in natural gas demand. Consequently, an initially positive GIRF emerged, with a negative peak around the third month. Notably, despite the surge in fossil fuel prices attributable to the Russia-Ukraine conflict, the underdeveloped infrastructure and limited integration of the renewable energy sector within the European energy mix precluded it from sufficiently bolstering the demand for additional energy.

The relationship between Geopolitical Risk (GPR) and gas demand is mixed. While, as expected, the effect of a positive GPR shock on natural gas demand was jagged during the Covid-19 period, it turned out to be positive during the Russia-Ukraine conflict. Geopolitical tensions and conflicts can create an environment of uncertainty, which may prompt countries to increase their energy reserves as a precautionary measure. The recent Russia-Ukraine war raised concerns about the stability of natural gas supplies, leading to a potential increase in demand as countries sought to secure their energy needs.

The findings obtained from the GIRFs analysis are enlarged with Figure 3.7, which reported the Generalized Forecast Error Variance Decomposition of the Gas Demand.

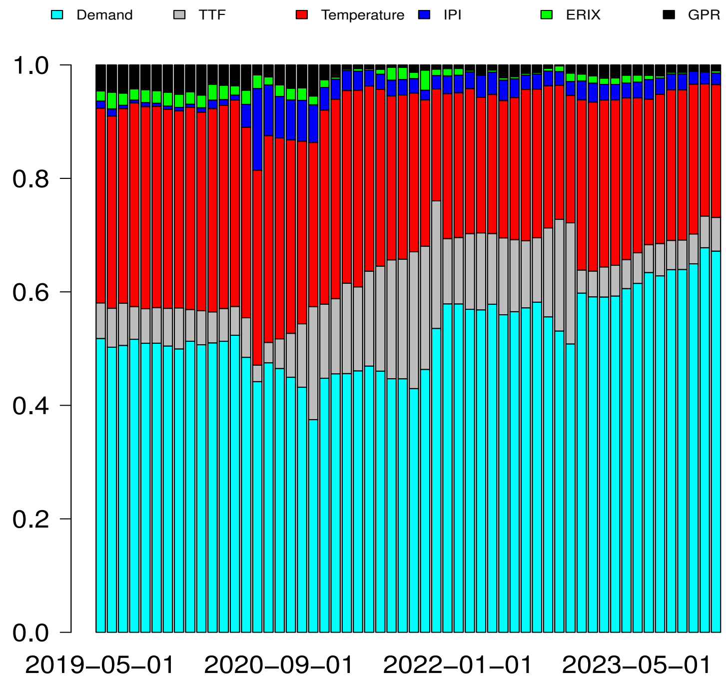


Figure 3.7: Gas Demand Forecast Error Variance Decomposition

Accordingly, we can discuss the percentage contribution of variables in gas demand determination. As expected, the role of temperature is the most relevant for gas demand setting. Indeed, the 35% of gas demand variation is explained by the average temperature, followed by TTF price, the second principal factor.

In this sense, the role of the Covid-19 pandemic is also demonstrated by the Unbiased Total Connectedness Index (Equation 3.15) reported in Figure 3.8.[10] Based on the Bai and Perron (2003) test for the simultaneous estimation of multiple breakpoints, we test if structural breaks emerged in the relationship in the test set. We set the number of maximum breaks allowed to 5 and consider a trimming parameter of 10%. The Bayesian Information Criteria (BIC) and the modified Schwarz criterion (LWZ) indicate that the optimal break number is 2. We report with red vertical lines in Figure 3.8 the breaks and the corresponding dates.

The first breakpoint in the series happens in March 2020, concomitantly with the Covid-19 period, and the second before the summer of 2021, when the economy started to rise after the fall during the Covid-19 pandemic. This result signals the role of the fall in the Euro area wealth (IPI) and the prompt European reaction to the Russian invasion that produced relevant effects in the markets. Recently, the TCI

[10] Supplementary material on pairwise relationships can be provided upon request.

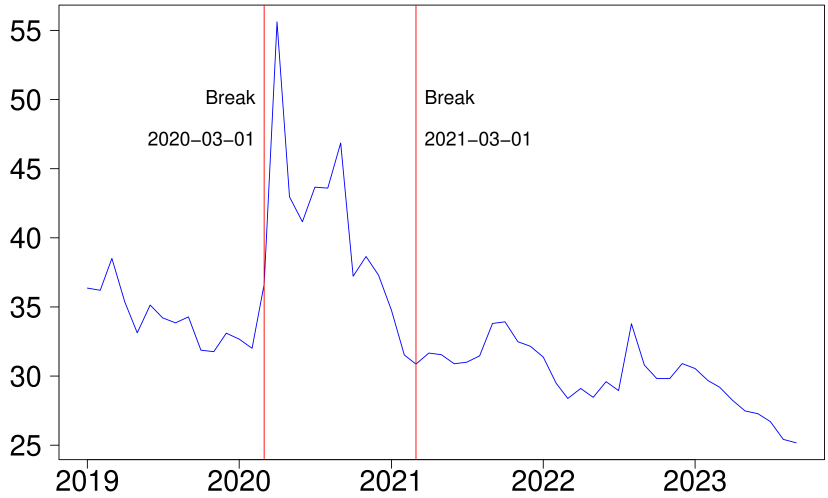


Figure 3.8: Unbiased Total Connectedness Index

declined, emphasizing the reduction in the interconnection of these series and the willingness of the Euro area to switch towards energy alternatives.

3.5.2 Wavelet analysis

In this section we estimate the dynamic phase relationship of TTF price on different inflation components. We proved in Section 3.5.1 the relevance of temperature in influencing the natural gas market. As a result, we consider both the standard Wavelet coherence plot between TTF price and inflation components (we define it "gross" TTF, see Figures 3.9 a.1, b.1, c.1) and the partialized version pruned by the temperature and GPR effects ("net" TTF, Figures 3.9 a.2, a.3, b.2, b.3, c.2, c.3).

The TTF wavelets between energy and headline inflation show comparable and similar behavior, whereas the core inflation is, as expected, poorly integrated within this context.[11] On average, the TTF price plays a relevant role in the headline and energy components, especially in the low-medium frequencies. The European sanctions imposed on Russia due to the invasion of Ukraine shook the political and economic patterns. Europe suffered a sudden energy shock, which led to a price increase. As a result, the TTF price played a leading role in driving up energy inflation in the medium term after the escalation of the war, as demonstrated by the wavelet plot in Figure 3.9 (a.1).

[11] We also tested for the natural gas demand effect on inflation without evidence of statistically significant impact. Estimations are available upon request.

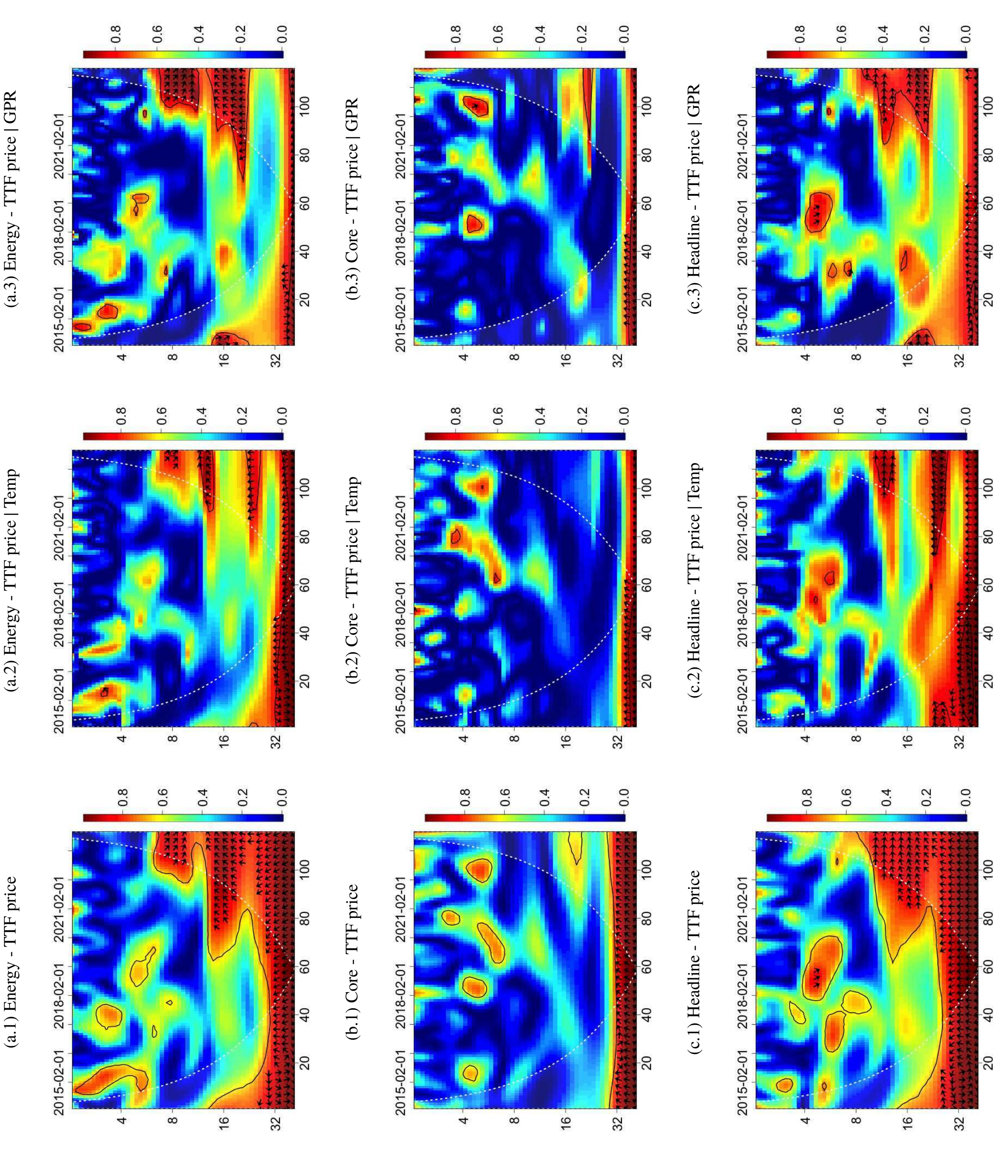


Figure 3.9: Wavelet Coherence Plots: inflations and TTF price

The behavior of the TTF price coherence and its partialized version differs in correlation intensity. Indeed, after removing the temperature and GPR effects, the degree of phase is significantly reduced, as demonstrated by the higher percentage of blue shades in the coherence plot. From an economic viewpoint, this finding underlines the speculative component on the TTF price that does not reflect the market price equilibrium. The temperature effect is directly attributable to climate change issues, which are becoming more and more relevant in influencing economic decisions (Sun et al., 2022). The increasing geopolitical tension led the markets to a radical change. In particular, the failure to develop a renewable energy industry such that it can make up for the problems with fossil energy sources has led to a relative increase (until summer 2022) in demand for natural gas as a cleaner alternative to other fossil fuels (see, among other, Wang et al., 2022a; Umar et al., 2022), influencing the corresponding price. Thus, higher demand generates higher prices, resulting in an inflation boost. As a result, the delay of EU policies and regulations aimed at reducing greenhouse gas emissions and promoting renewables may have contributed to an increased dependency on natural gas, further influencing the correlation.

Figure 3.10 reports the wavelet coherence plots for inflation components, temperature, and GPR. The GPR is in phase with energy inflation during the recent Russia-Ukraine conflict in the short term. In general, the GPR influences also the inflation components in the longer term. This evidence signals the role of geopolitical ties between countries in the behavior of the real economy. Quite the opposite, the temperature is inversely correlated (out-of-phase) with all inflation components, especially in the recent period in the short run, evidencing the containing role of temperature for the inflation boom.

In addion, we consider TTF price, GPR, and Temperature plus one inflation component (in order: energy, headline, and core) in three different TVPVAR models:

- MODEL A: Energy Inflation, TTF price, GPR, and Temperature;
- MODEL B: Core Inflation, TTF price, GPR, and Temperature;
- MODEL C: Headline Inflation, TTF price, GPR, and Temperature.

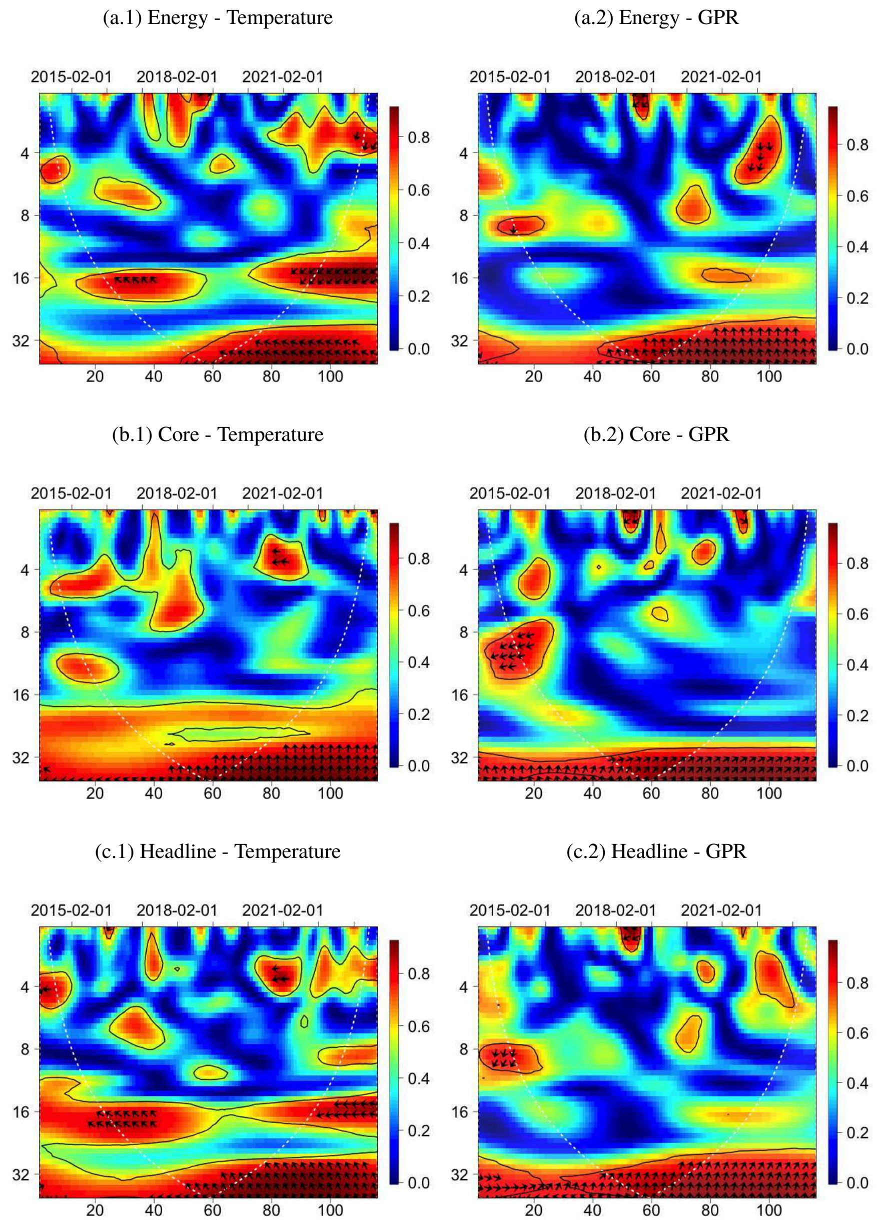


Figure 3.10: Wavelet Coherence Plots: Inflations, Temperature and GPR

The training and test sets are the same as those discussed on page 135. Figure 3.11 reports the time-varying coefficients of TTF, Temperature, and GPR on the relative inflation components with a 90% confidence interval.

The first row of Figure 3.11 shows the time-varying coefficients of TTF, Temperature, and GPR on Energy inflation. While the impact of TTF and GPR is statistically null for the majority of the period, the role of temperature contributes to reducing energy inflation in the 2022 winter season, confirming the out-of-phase relationship found in the Wavelet analysis (Figure 3.10-a.1).

Moreover, the role of temperature in reducing inflation is higher in the headline case, especially during 2022. During this year, the GPR contributed to increasing the average level of headline inflation, being a crucial factor in the current inflation increase. Since we have included TTF, temperature, and GPR in these systems, the marginal impact of the TTF price on the inflation components underlines how temperature and GPR are relevant factors in the current economic environment.

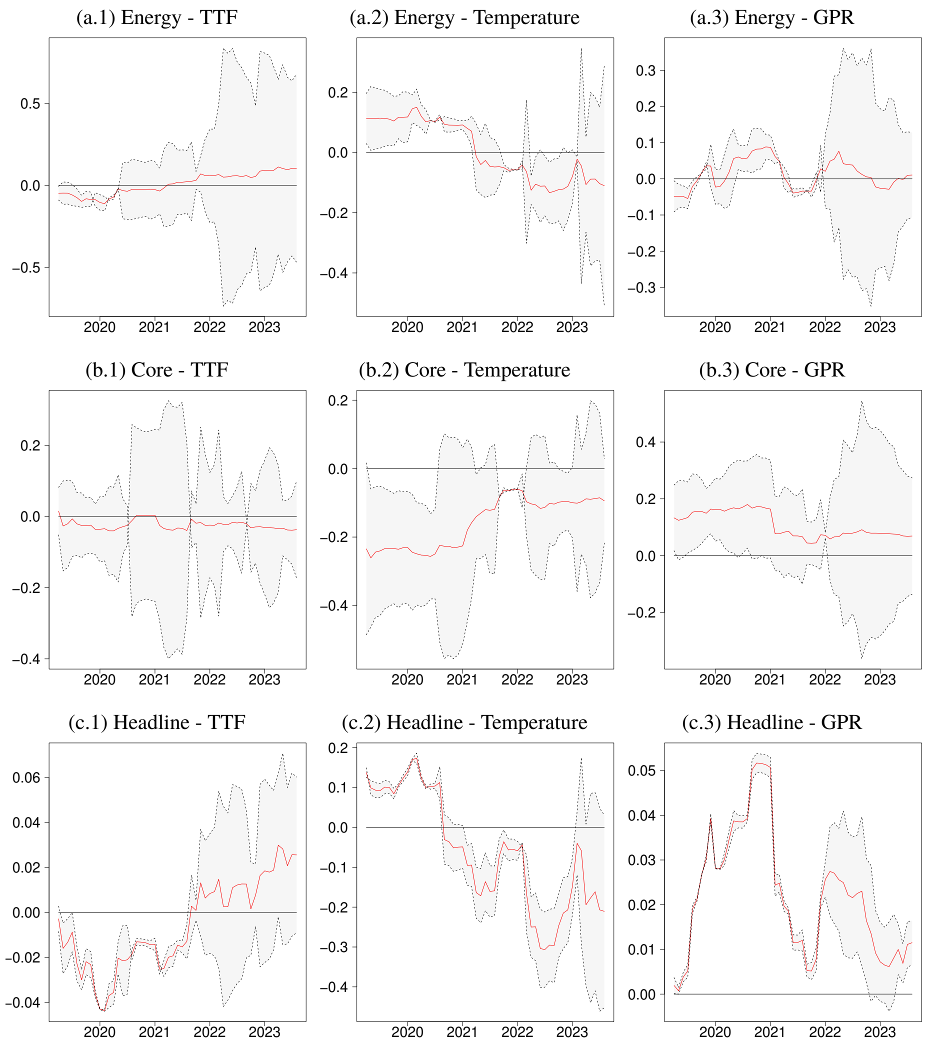
From a macroeconomic viewpoint, our result demonstrates that the recent higher temperatures were relevant to restricting the inflation boom, while the ongoing geopolitical tensions contributed heavily to the inflationary rise. As a result, policymakers and governments should reduce the reliance of domestic economies on exogenous shocks.

Furthermore, looking at the confidence interval of the coefficients, the uncertainty in the markets led by the Russia-Ukraine war increased. This occurrence leads to higher standard deviations and higher intervals that make the variables less significant, implying the role of exogenous shocks in the development of inflation components, such as the expectations of market actors. This result is mainly due to the de-anchoring of inflationary expectations of economic actors (Blanchard and Pisani-Ferry, 2022).

The GFEVD results reported in Figure 3.12 suggest that despite the lack of significance in the individual coefficients, shocks or innovations in TTF price impact the overall forecast error variance of the inflation components. Despite the TTF price might not help predict inflations in the short term, once considered for GPR and Temperature, its unexpected shocks are crucial for the overall volatility of the model. This result could have important implications for understanding the dynamics of the relationship between energy prices (TTF) and inflation over a longer time horizon.

We extend the results for the US obtained in Giri (2022). Using wavelet analysis, he found that core inflation is weakly correlated with headline inflation, especially at the lower frequencies. On the contrary, energy inflation is strongly correlated with headline inflation at a broad range of frequencies.

Figure 3.13 reports the wavelet plots for headline, core, and energy inflation. Since core inflation is adjusted for energy and volatile components, we do not include



Note: The red line is the estimated time-varying coefficients while the grey shades is the 90% confidence interval.

Figure 3.11: Time-Varying Coeffients of Inflation VAR models.

its coherence with energy inflation. While we confirm the results of Giri (2022) for the relationship between headline and energy inflation, confirming doubts about the exemption of energy inflation from a trend inflation measure, we cannot validate his evidence for the headline and core inflation linkage. Indeed, we find evidence of a strong phase relationship between headline and core inflation in the short term, at least until the onset of the Russia-Ukraine war, which corresponds to the misalignment of inflation expectations. From an economic perspective, this result is relevant because it confirms the thesis that controlling core inflation could allow central bankers to keep inflation stable in the medium term.

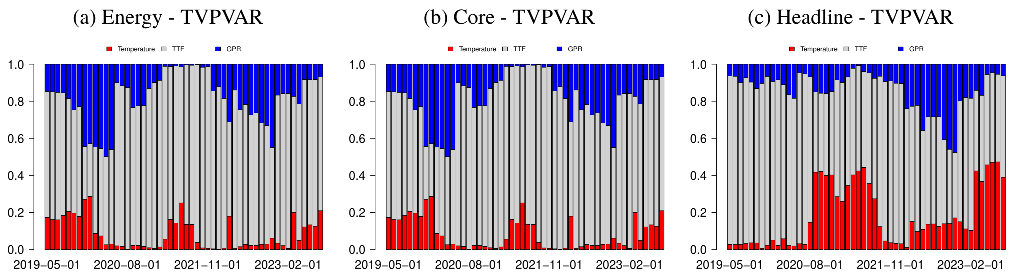


Figure 3.12: Time-Varying FEVD of Inflation VAR models.

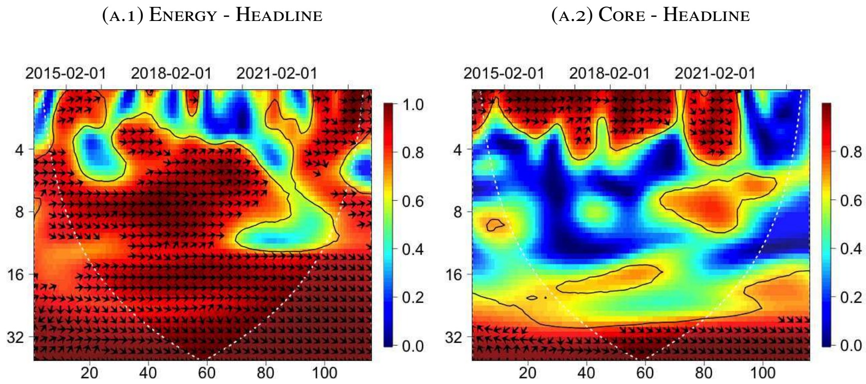


Figure 3.13: Wavelet Coherence Plots between inflation components

3.6 Conclusions and policy implications

In this study, we analyze the role of temperature in the current development of the energy market. First, we discuss the importance of temperature on gas demand. Second, we describe the role of temperature in containing the inflation surge especially after the Russia-Ukraine war.

As evidenced by the Generalized Impulse Response Functions (GIRFs), we found an immediate and persistent effect of temperature shocks on gas demand, with a more prolonged impact observed during the Russia-Ukraine conflict. The importance of temperature in containing natural gas demand was confirmed by the variance decomposition results.

The wavelet analysis provided additional insights into the dynamic relationships between TTF price, temperature, and inflation components. The role of temperature in mitigating inflation, especially during the 2022 winter season, highlighted the broader implications of climate-related factors on economic dynamics. Moreover, the impact of exogenous shocks, such as the Russia-Ukraine conflict, on inflationary expectations was evident in the time-varying VAR models and Generalized Forecast Error Variance Decomposition results.

This work leaves room for some policy suggestions. The persistent impact of temperature shocks on gas demand, as revealed by the GIRFs and variance decomposition, highlights the significance of climate considerations in energy planning. Policymakers should prioritize climate-resilient energy infrastructure and formulate policies that account for the varying effects of temperature on gas demand. On this line, the positive impact of the ERIX on natural gas demand during the Russia-Ukraine conflict indicates the importance of renewable energy infrastructure. Governments should consider increasing investments in renewable energy projects to enhance energy security and reduce dependency on fossil fuels during geopolitical crises. Strengthening the integration of renewables within the European energy mix can contribute to long-term sustainability.

The relationship between Geopolitical Risk (GPR) and gas demand underscores the need for proactive geopolitical risk management in energy policies. Policymakers should closely monitor geopolitical developments and develop strategies to mitigate the potential disruptions in energy supply chains. Diversification of energy sources and diplomatic efforts to ensure stable international relations can contribute to reducing the impact of geopolitical risks on gas demand.

Our work has some limitations. Our analysis focuses on the aggregate European level, whereas future research could study these relationships in a specific country, reducing the loss of information in the aggregation of results. In addition, future research could address the issue of the differentiation of gas demand for domestic or industrial use to obtain a more detailed market description.

3.A Level Series

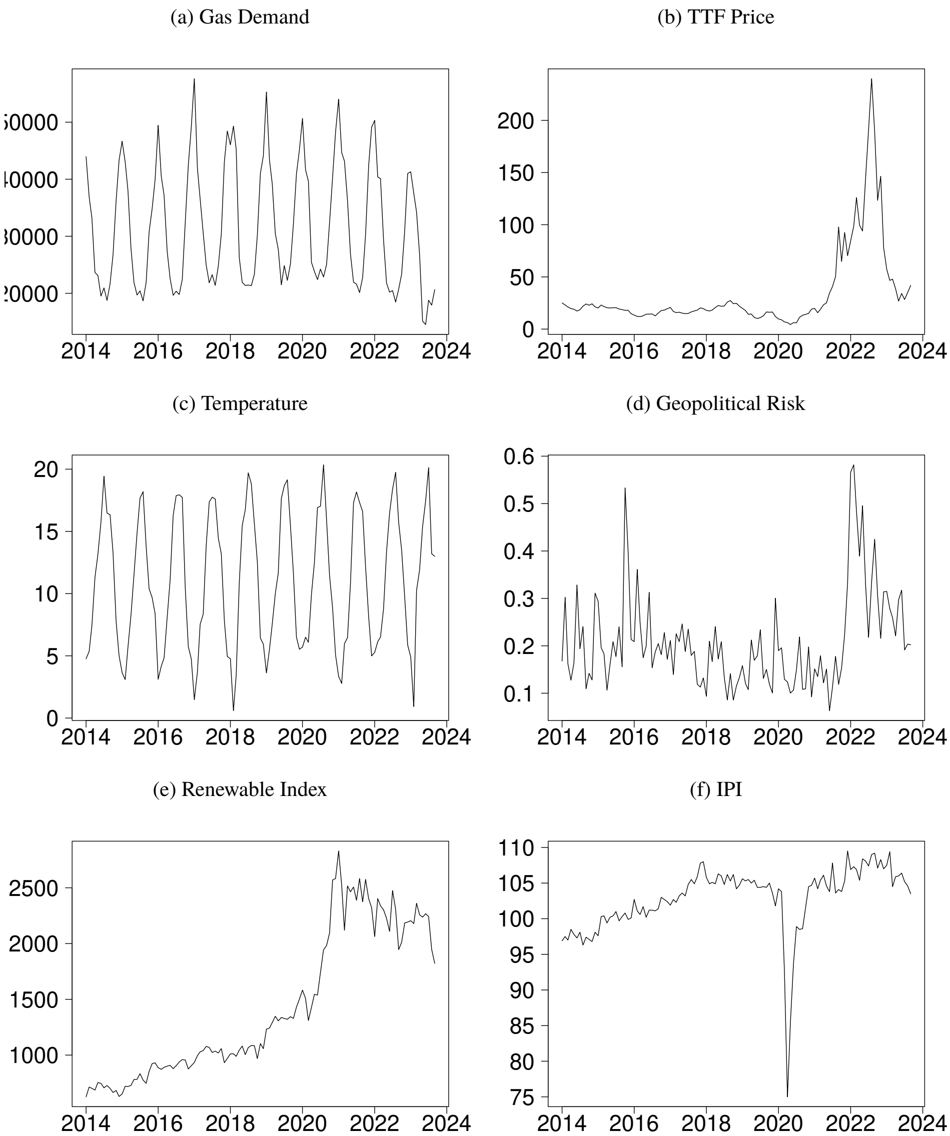


Figure 3.14: Level series

	Gas Demand	TTF	Temperature	IPI	ERIX	GPR
Mean	31563.7552	33.8511	10.9600	102.8274	1426.3562	0.2087
Med	29327.3600	19.7040	10.8337	104.2000	1086.5200	0.1880
SD	10736.3372	40.1434	5.4180	4.6656	648.2268	0.1012
Max	57628.4000	239.9070	20.3471	109.5000	2829.7200	0.5817
Min	14524.7854	4.3850	0.5914	75.0000	625.7800	0.0632
ADF	-8.4479 ***	-2.6123	-12.4511 ***	-2.8776	-1.6633	-3.1513 ***
PP	-39.7024 ***	-13.6833	-41.6302 ***	-24.6123 **	-9.2374	-46.3219 ***
KPSS	0.0641	0.8373	0.0405	0.7079 ***	2.1458	0.3231

*p<0.1; **p<0.05; ***p<0.01

Table 3.7: Descriptive statistics and unit root tests of original series.

3.B Gretl main loop

```
function matrices Bayes(matrix x, scalar nlag)
    # Bayesian Prior. Input: matrix of time series data
    # The input x is a matrix of time series data with n observations and p variables.
    # The function also takes as input the number of lags nlag
    # The function first constructs a matrix Zt that includes
    # lags of the p variables up to order nlag.

    scalar p = cols(x)
    scalar n = rows(x)
    scalar size = n - nlag
    scalar nlag_1 = nlag+1
    matrix yt = {}
    yt = x[nlag_1:n,]'
    scalar m = p + nlag*(p^2)
    matrix Zt = {}
    loop i = nlag_1 .. n
        ztemp = I(p)
        loop j = 1 .. nlag
            scalar row_element = i-j
            matrix xlag = x[row_element,1:p]
            matrix xtemp = zeros(p,p*p)
            loop k = 1 .. p
                xtemp[k,(((k-1)*p)+1):(k*p)] = xlag
            endloop
        ztemp = ztemp ~ xtemp
        endloop
        Zt = Zt | ztemp
    endloop

    matrix vbar = zeros(m,m)
    matrix xhy = zeros(m,1)
    loop i = 1 .. size
        matrix zhat1 = Zt[((i-1)*p+1):(i*p),]
        vbar = vbar + zhat1'*zhat1
        matrix dt = yt[,i]
        xhy = xhy + zhat1'*dt
    endloop

    vbar = ginv(vbar)
    aols = vbar*xhy
    matrix bprior = aols[-seq(1,p,1),]
    matrix vprior = vbar[-seq(1,p,1),-seq(1,p,1)]
    matrix SSE2 = zeros(p,p)
    loop i = 1 .. size
        zhat1 = Zt[((i-1)*p+1):(i*p),]
        SSE2 = SSE2 + (yt[,i] - zhat1*aols)*(yt[,i] - zhat1*aols)'
    endloop
    hbar = SSE2/size
    matrix vprior = vbar[-seq(1,p,1),-seq(1,p,1)]
    matrix Q_t = hbar

    matrices A = defarray(bprior,vprior,Q_t)
    return A
end function
```

Figure 3.15: Prior definition

```
##################### TVP VAR COMPUTATION #####################
function matrices TVPVAR(matrix x,
                         scalar lag,
                         string prior,
                         scalar decay_factor,
                         scalar forgetting_factor)
    # x is the time series matrix. It must be indexed with data (T) and must be observed for N series. TxN
    # lag p is the Autoregressive order.
    # prior is the prior probability used: in the code recall the Bayesian, Minnesota, or Uninformative priors functions.
    # decay_factor and forgetting_factor are for Kalman filter.

    scalar p = lag
    scalar n = cols(x)
    scalar t = rows(x)
    scalar l_2 = decay_factor
    scalar l_4 = forgetting_factor

    if prior == "Bayes"
        Bayes = Bayes(x,p)
        beta_0_mean = Bayes[1]
        beta_0_var = Bayes[2]
        Omega_0 = Bayes[3]
    elif prior == "Minnesota"
        Minnesota_prior = Minnesota(0.1, n, p)
        beta_0_mean = Minnesota_prior[1]
        beta_0_var = Minnesota_prior[2]
    else
        Uninformative_prior = Uninformative(n, p)
        beta_0_mean = Uninformative_prior[1]
        beta_0_var = Uninformative_prior[2]
    endif
    print "TVP-VAR computation"

    matrices A_t_mean = array(t)    #Is the time-varing matrix of estimated parameters
    matrices Omega_t = array(t)     #Is the time-varing covariance matrix of the error term of y_t = A_t x_{t-1} + e_t
    matrices Sigma_t = array(t)     #Is the time-varing covariance matrix of the error term of vec(A)_t = vec(A)_t + nu_t
    matrices Kalman_t = array(t)    #Is the time-varing multivariate Kalman gain
    matrices C_t = array(t)
    matrix A_pred = zeros(n^2,t)    #Is the matrix
    matrix A_update = zeros(n^2,t)
    matrix Varepsilon_t = zeros(n,n)
    matrix A_col = zeros(n^2*p,1)
    matrix y = zeros(n,1)

    loop for i = 1 .. t #Inizialization of arrays
        A_t_mean[i] = zeros(n,n*p)
        Omega_t[i] = zeros(n,n*p)
        Sigma_t[i] = zeros(n^2*p,n^2*p)
        C_t[i] = zeros(n^2*p,n^2*p)
        Kalman_t[i] = zeros(n^2*p, n)
    endloop

    # Inizialization of the variables. It means the starting point of the Kalman filter where t=1
    Omega_t[1] = Omega_0
    Sigma_t[1] = beta_0_var
    A_pred[,1] = beta_0_mean

    matrix yy = x[(p+1):t,]
    matrix xx = x[1:(t-p-1),]

    loop for i = 2 .. (t-1)
        if i <= (p+1)
            A_pred[,i] = A_pred[,(i-1)]
            A_update[,i] = A_pred[,i]
            Sigma_t[i] = Sigma_t[(i-1)]
            Varepsilon_t = x[i,]'x[i,]
            Omega_t[i] = l_2*Omega_t[(i-1)] + (1-l_2)*Varepsilon_t
        elif i>(p+1)
            Varepsilon_t = yy[(i-p),] - xx[(i-p),]*A_t_mean[(i-1)]
            SSR = Varepsilon_t*Varepsilon_t'
            Kron = x[i,] ** I(n)
            Sigma_t[i] = (1/l_4)*Sigma_t[(i-1)]
            Omega_t[i] = Kron*Sigma_t[i]*Kron' + l_2*Omega_t[(i-1)] + (1-l_2)*SSR
            Kalman_t[i] = Sigma_t[i]*(Kron'*inv(Omega_t[i]))
            e_hat = yy[(i-p),] - xx[(i-p),]*A_t_mean[i]
            A_update[,i] = A_pred[,i] + Kalman_t[i]*e_hat'
            C_t[i] = Kalman_t[i]*Kron
            Sigma_t[i] = (I(n^2*p) - C_t[i])*Sigma_t[i]
            Omega_t[i] = l_2*Omega_t[i] + (1-l_2)*e_hat*e_hat'
        endif
        A_col = decay_factor*A_update[,(i-1)]
        print
        A_t_mean[i] = mshape(A_col, n, n*p)
        print i | x[i,]*A_t_mean[i]
    endloop

    #Value2Return = defarray(A_t_mean, Omega_t)
    #return Value2Return
    matrices ReturnValue = array(t)
    loop for i = 1..t
        ReturnValue[i] = A_t_mean[i] ~ Omega_t[i]
    endloop

return ReturnValue
end function
```

Figure 3.16: TVPVAR main loop

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