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Relatio sine qua non. Exploring interconnectedness in sustainable development

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Abstract
This study sheds light on the interplay among environmental sustainability, technological innovation, and regional economic development within the European Union NUTS2 regions. By analysing data on various socioeconomic and environmental variables, we uncover different stages of transition coexisting within the European Union and within the same country, emphasizing the significance of green transition strategies that account for regional cohesion. Our findings underscore the need for policies that foster just and inclusive development, considering the multidimensional challenges of sustainability.

Keywords: just transition, regional sustainable development
JEL Classification Codes: R11

1. Introduction

A ubiquitous representation of sustainability involves the intersection of three circles representing the environmental, social, and economic dimensions. Although this framework lacks a clear origin in the academic literature (Purvis et al., 2019), it now guides sustainability policies, emphasizing that environmental protection, social equity, and economic viability are complementary priorities. As the green transition becomes the imperative of the development strategies of the European Union (EU), competitiveness requires innovative products that significantly reduce resource and energy consumption. The underlying assumption is that a greener innovative Europe can lead the way to new modes of development that conjugate human well-being,economic growth, and environmental sustainability.

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Even so, the EU environmental agenda may not distribute benefits equally, both when it comes to interpersonal inequality and regional cohesion. While the EU and national governments define policy measures and regulations aimed at promoting the sustainable transition, their effects are likely to be unevenly distributed among individual agents (households, workers, and firms), putting some local and regional communities more at risk than others.

The link between green transition and social justice is well documented in the literature. For instance, Oueslati et al. (2017) find a positive correlation between inequality and energy tax reforms, while Faiella and Lavecchia (2021) emphasize the need for compensation mechanisms to alleviate the disproportionate impact of green energy taxation on poorer households. Environmental regulations can shift sector compositions, leading to (geographically concentrated) job creation or loss (Vona, 2021), with local labor markets dependent on energy and carbon-intensive industries being particularly vulnerable (OECD, 2012). Other geographical factors may exacerbate job losses in these sectors, affecting reconversion and migration costs, and altering income distribution. Castellanos and Heutel (2021) suggest that the local impact of green transition policies varies based on labor mobility, green innovation and technologies (Costantini et al., 2018), market concentration and firm size distribution (Zaman and Borsky, 2021), and the demand for green skills (Marin and Vona, 2019). Markkanen and Anger-Kraavi (2019) frame the inequality-transition relationship within the broader context of climate change mitigation policies, emphasizing the importance of spatial analysis for understanding local labor market effects and regional disparities. This aligns with a growing body of research on the distributive effects of climate change, natural disasters, green innovation, and environmental regulation (Cappelli et al., 2021; Napolitano et al., 2022; Paglialunga et al., 2022). Knowledge and innovative capacity emerge as a pivotal factor in the so-called twin (i.e., green and digital) transitions, but they are also unevenly distributed across regions (Balland et al., 2019).

Core-periphery dynamics highlight that peripheral areas often face social, economic, and political marginalization, limiting their influence on resource allocation decisions. This holds valid true in the context of decarbonisation policies, as Yenneti et al. (2016) show that low-carbon transitions can marginalize regions with less socio-economic or political power. O'Sullivan et al. (2020) further highlight the interrelation between spatial justice and energy justice in the context of energy system transformations.

Although decarbonization policy goals are often set at the EU or national level, their success hinges on recognizing local opportunities and threats. Therefore, subnational analysis is essential for monitoring and supporting impact assessment and policy implementation within the multifaceted challenges associated with environmental and social transitions.

This study aims to explore the interplay of factors contributing to a territory's vulnerability as the green transition unfolds, aligning with the goal of "ensuring a fair and socially acceptable transition for all in the spirit of inclusivity and togetherness" (EC, 2018).

2. Methods

To explore our research question, we rely on contributions working with Dynamic Factor

Analysis (DFA). Originally conceptualised by Coppi and Zannella (1978), DFA aims to simplify the complexity of high-dimensional data by summarizing multiple correlated variables into a smaller set of common factors. This method identifies underlying trends in the data, here representing the core dynamics driving sustainable regional transitions. Formally, DFA dissects a data matrix X into three arrays:

$$X(I,J,T) = \{x_{ijt}\}, \quad with\ i = 1,2,\dots,I, \quad j = 1,2,\dots,J, \quad t = 1,2,\dots,T \quad (1)$$

where *xijt* represents a cell in *X*, corresponding to the *i*-th unit of observation, for the *j*-th variable at time *t*. As a result, the total variability matrix of *X*, *S*, encompasses three distinct components:

$$S = S_I^* + S_T^* + S_{IT} \quad (2)$$

where S_I^* captures the static structure of the data, reflecting unit-level variability across variables, independent of time; S_T^* represents temporal variability reflecting common trends in all units; and S_{IT} denotes the variability of unit-time couples throughout different variables. The key innovation in the DFA approach is the contraction of this fundamental decomposition into two sources of variability:

$$S = S_I^* + S_T^* + S_{IT} = S_T + S_T^* \quad (3)$$

S_T represents the average dispersion matrix within times (within variability) and is modelled through Principal Component Analysis (PCA). S_T^* captures the variability between times (between variability), modelled through an OLS regression of the form:

$$\bar{x}_{.jt} = \alpha_j + \beta_j t + \varepsilon_{jt} \quad (4)$$

where $\bar{x}_{.jt}$ is the average value over variable j and time t. Operationally, we follow Federici and Mazzitelli (2005) and estimate the coefficients $\hat{\alpha}$ and $\hat{\beta}$ by regressing the principal components onto the time vector t.[1]

The DFA approach allows us to identify the key factors that explain most of the variability in socioeconomic and environmental indicators across regions. Having this information, we can assess regional performance and examine how different regions are advancing in the green transition.

This approach also allows us to handle the complexities of the green transition overcoming collinearity, which is especially relevant for multifaceted phenomena like sustainability, and capturing the dynamic components of transition, thus accounting for forms of path-dependence that are established in the literature on knowledge building and human capital.

[1] A similar application can be found in Vanli (2024).

3. Data

Our dataset incorporates regional data for EU NUTS2 regions, supplemented with national data when region-based information is missing, over a 20-year time frame (2000 to 2019). The dataset includes 34 variables on business structure, economic account, demographics, employment, inequality and social exclusion, gender equality, innovation, (green) taxation, energy statistics, and greenhouse gas emissions (see Table 1 for the variables description).[2]

We resort to Eurostat's regional database for socioeconomic indicators, including population, Gross Domestic Product (GDP), disposable income, gender employment gaps, demographics, and employment (NUTS2 level). Significantly to our analysis, Eurostat data include variables collected in the Regional Innovation Scoreboard (RIS). The RIS database focuses on research and innovation-related metrics, including employment in technology-intensive sectors, Research & Development (RD) personnel, and tertiary education enrolment. These indicators provide insights into the innovation landscape across various regions, spanning both public and private sectors.

The EDGAR (Emissions Database for Global Atmospheric Research) database collects emission data from various sources, including national inventories, industry reports, scientific literature, and satellite observations. It then processes and harmonizes this information to generate detailed estimates of emissions for a wide range of pollutants. The measurements available for the NUTS2 level are carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), and fluorinated greenhouse gases (F-gases).

The OECD REGPAT (Regional Patent) database is widely used for research on the geographic distribution of innovation, as it provides regional-level data on patent applications, allowing for analysis of innovation and technological activity across geographies. REGPAT collects information on patent applications at the European Patent Office (EPO) as well as within the Patent Cooperation Treaty (PCT). Furthermore, it informs on the technological class of patents, by cooperative patent classification codes (CPC). We use the Spring 2023 version of the dataset and focus on EPO applications (by priority year).[3] Starting from REGPAT data, we assign patent applications to each NUTS2 region, obtained by counting those occurred between 2000 and 2019 by an inventor located in the region. This passage is repeated after filtering out patent applications with a CPC code equal to Y02, which indicates inventions dedicated to climate change adaptation and mitigation. In this way, we compute an eco-innovative patent count.[4]

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[2] For regional variables expressed as absolute values, we take the per capita measure by dividing by the yearly regional population.

[3] Three NUTS2 revisions took place at the time of our analysis, making some entries in REGPAT inconsistent. To overcome this, we recode some REGPAT regional identifiers to match the current classification.

[4] The literature exploiting patent information is often concerned by the data truncation due to the delayed publication of patent applications (Castellani et al., 2022). Considering that this phenomenon has no reason to present a spatial connotation, we decide not to act in this respect.

Table 1. List of variables

Name	***Description***	***Unit of measure***
EUROSTAT		
Disp	Disposable income in NUTS2 regions	Million PPS
Egap	Gender employment gap by NUTS2 regions	Percentage
Gdp	Gross domestic product in NUTS2 regions	Million euros
Htec	Employment in technology and knowledge-intensive sectors by NUTS2 regions and sex	Thousands of persons
lllearn	Participation rate in education and training by NUTS2 regions	Percentage
median	Median age of the population by NUTS2 region	Years
nacea	Employment by economic activity and NUTS2 regions (NACE Rev. 2) – Agriculture, Forestry and Fishing	Thousands of persons
nacebe	Employment by economic activity and NUTS2 regions (NACE Rev. 2) – Industry (except Construction)	Thousands of persons
nacef	Employment by economic activity and NUTS2 regions (NACE Rev. 2) – Construction	Thousands of persons
Ted	Tertiary educational attainment, age group 25-64 by NUTS2 regions	Percentage
unemp	Unemployment rate by NUTS2 regions	Percentage
OECD REGPAT		
Pat_count	Number of patent applications at the European Patent Office, by priority year	Integer
Ecopat_count	Number of eco-innovative patent applications at the European Patent Office by priority year	Integer
OECD Environmental Policy Stringency Indicators		
c_co2ets	Carbon dioxide (CO2) Trading Scheme	Integer
c_co2tax	Carbon dioxide (CO2) tax	Integer
c_diesel	Diesel tax	Integer
c_envpol	Adoption of solar and wind energy support measures	Integer
c_lowrd	Low-carbon R&D expenditures	Integer
c_market	Market-based instruments	Integer
c_nonmark	Non-market based instruments	Integer
c_noxlim	Emission limit value NOx	Integer
c_noxtax	NOx taxation	Integer
c_pmlim	Emission limit value PM	Integer
c_renets	Renewable Energy Trading Scheme	Integer
c_sox	Emission limit value SOx	Integer
c_solar	Solar Energy support (Auctions & FITs)	Integer
c_sulflim	Emission limit value sulphur	Integer
c_sulftax	Sulphur Oxides (SOx) Tax	Integer
c_tech	Technology support policies	Integer
c_wind	Wind Energy support (Auctions & FITs)	Integer
EDGAR (Emissions Database for Global Atmospheric Research)		
ch4	Methane emissions by NUTS2 regions	Kt CO2eq
co2	Carbon dioxide emissions by NUTS2 regions	Kt CO2eq
fgas	Fluorinated gases emissions by NUTS2 regions	Kt CO2eq
n2o	Nitrous oxide emissions by NUTS2 regions	Kt CO2eq

Lastly, the OECD environmental policy stringency (EPS) indicators offer insights into countries' regulatory landscape surrounding environmental protection and sustainability. OECD assigns a national score based on the implementation of virtuous policy measures, such as emission caps, green taxation schemes, RD expenditures, and support for renewable energy sources. These indicators gauge the degree of the efforts to mitigate pollution and foster sustainable development practices. We assign to every region the corresponding national score.

4. Results

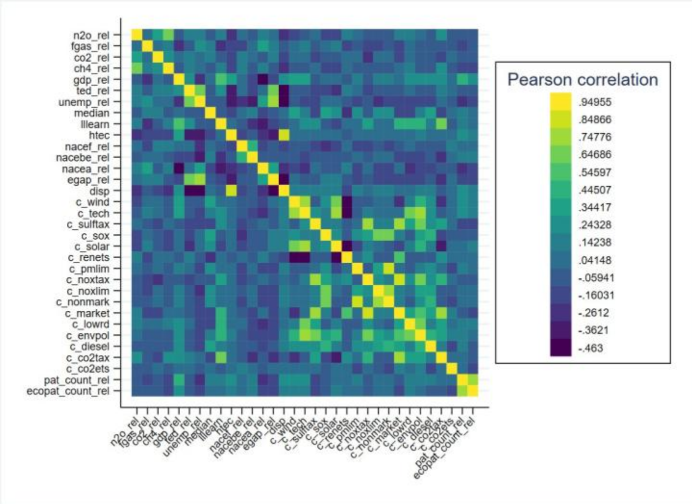
We decompose the total variability of the panel data into a static component, modelled through PCA,[5] and a dynamic component, modelled through OLS (Ordinary Least Square) regression of the time vector over the values of the first component throughout the years, for each region.

The static variability reveals strong correlations between the variables considered (Figure 1). As the plot shows, wide areas of correlation between crucial variables exist. This is true in the case of EPS indicators, which are in most cases highly collinear, but also when it comes, for instance, to median age of the population and policy stringency, GDP and innovation metrics, disposable income and high-tech employment, and most emissions variables among themselves. This descriptive evidence validates our framework, suggesting that green transition needs to be investigated through tools able to deal with high-dimensionality and interdependencies, like PCA.

Considering the first component (which account for 26% of the variability in our data), Table 2 highlights that the highest PCA loadings correspond to indicators of national policy stringency. This suggests that national-level compliance with sustainability goals plays a significant role in shaping transition dynamics, while regional variables targeting innovative capacity and social justice also emerge as important factors. Indeed, apart from variables commonly associated with higher overall well-being (e.g., GDP) knowledge capital building and social equity emerge as key factors, with lifelong learning and participation in education and training scoring the highest loading among regional-level variables.

[5] Performing a PCA requires a balanced dataset. To accomplish this with the smallest loss of information possible, we adopt three strategies. In order of preference: 1) we interpolate those variables that present occasional breaks in the time series but are otherwise collected regularly and throughout most of the regions; 2) we drop variables that are too sparsely recorded; 3) we drop regions presenting a critical number of blanks. The results of this process are summarized in Table 1. The dropped regions are in grey in Figure 3.

Figure 1. Heatplot of static variability



Source: authors

Table 2. Loadings on the first principal component

Variable name	Factor loading	Variable name	Factor loading	Variable name	Factor loading
c_envpol	0.3472	lllearn	0.1508	pat_count_rel	0.0684
c_nonmark	0.3447	c_lowrd	0.1465	ecopat_count_rel	0.0646
c_sox	0.3293	gdp_rel	0.1433	nacebe_rel	-0.0628
c_pmlim	0.3148	c_noxtax	0.1323	co2_rel	-0.0604
c_noxlim	0.2978	c_co2tax	0.1212	unemp_rel	-0.0500
c_sulflim	0.2891	c_renets	0.1011	disp	0.0497
c_tech	0.2113	egap_rel	-0.0995	ch4_rel	-0.0490
median	0.2009	c_diesel	-0.0974	htec	0.0259
c_co2ets	0.1941	c_sulftax	0.0954	ted	0.0221
c_market	0.1819	nacea_rel	-0.0822	n2o_rel	-0.0191
c_solar	0.1668	c_lowrd	0.1465	fgas_rel	-0.0170
c_wind	0.1544	gdp_rel	0.1433		

Source: authors

The signs of the loadings associated with the EDGAR variables give validity to our framework, indicating that higher emissions per capita correspond to worse-performing regions. The same applies to the gender employment gap: a negative loading warns on how gender marginalization works against sustainable development.[6] Interestingly, although energy consumption and energy production did not make the cut of the variables in our dataset, the EDGAR emission variables indirectly proxy the energy profile of regions. For example, one could argue that renewable power plants play a role in determining the presence of most Southern Italian regions in the best-movers cluster. There appears to be a story behind sectoral

[6] A similar inverse relationship is found for components 2 to 9, which together account for 70% of the variability of the data.

composition variables and patent applications, too. While higher ratios of workers in the primary and secondary sectors are negatively correlated to the diffusion index, patent applications (total and eco-innovation) move in the same direction.

The dynamic variability is derived by regressing the 20-year time vector on a weighted composition of the first nine components, which together account for 70% of the variability in our data.[7] Following Qin et al. (2024), the weights are assigned based on the relative explained variability. The regression results show a very low significance of the angular coefficient, indicating that regional performances do not experience a significant trend over the period considered. This result suggests a relatively slow responsiveness to decarbonisation and transition agendas, likely due to underlying structural changes hindering rapid adaptation to energy policies and technological advancements.

We store the coefficients of the dynamic variability regressions and compute two new variables: i) the slope of its function, as an expression of the sharpness of the regions' transition path (*b,* measured on the horizontal axis in Panel (a) in Figure 2); ii) the integral of the curve, to measure the overall "level" of sustainable transition performance over time (*integral,* measured on the vertical axis in Panel (a) in Figure 2).

Considering the median value of both the level and the slope, we define four regional clusters as described in Figures 2 and 3. The resulting four clusters are described as follows:[8]

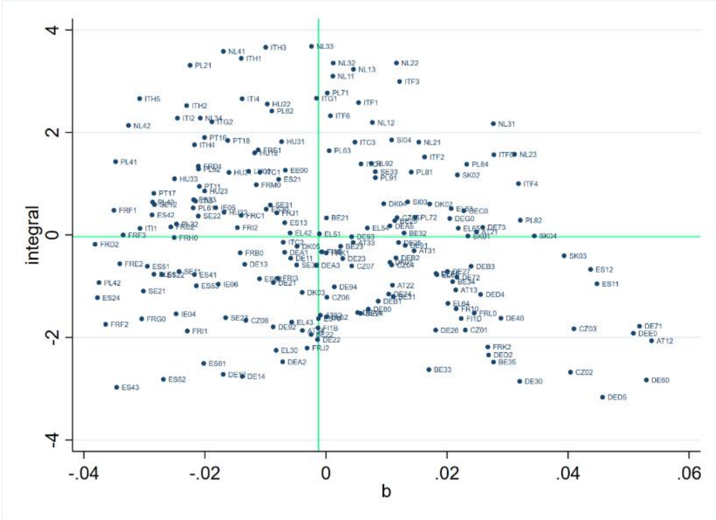
- High performance and high-speed regions: best movers
- High performance and low-speed regions: first movers
- Low performance and high-speed regions: fast movers
- Low performance and low-speed regions: last movers

[7] Since thirty of our components have eigenvalues greater than one, the conventional Kaiser criterion, which suggests retaining components with eigenvalues greater than one (Hsieh et al., 2004; Kaiser, 1960), is inconvenient. Therefore, we use the alternative selection criterion (Jolliffe, 2002), which states that components that explain a minimum of 70% of the variation should be retained.

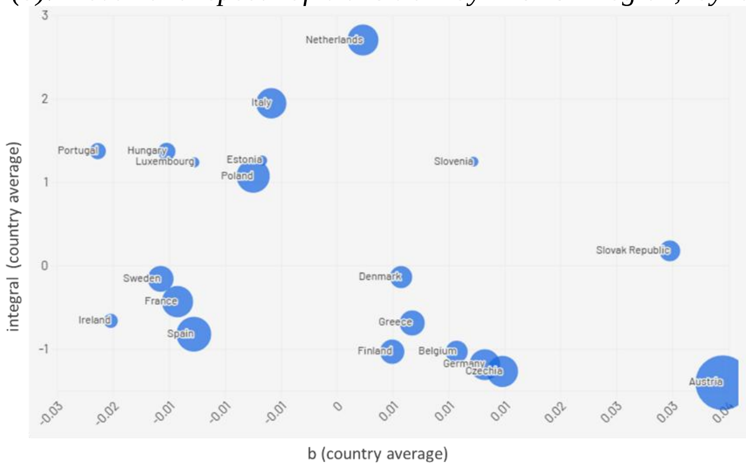
[8] To further assess the robustness of the clusters' composition, we have conducted additional sensitivity analyses using alternative approaches: i) including all components that collectively account for 50% of the variability; ii) including all components with an eigenvalue greater than 1; iii) including all components; iv) including only the first component. In cases i) to iii), each component is weighted by their relative explained variability. The results of these robustness checks confirm the stability of our classification. Specifically, the classification of regions into clusters remains consistent in 99% of cases across all the alternative specifications i) to iii). When comparing these classifications to the one based solely on the first component, we find that the classification remains unchanged in 75% of cases.

Figure 2. Scatterplot of dynamic variability - level over speed of transition

Panel (a): Level and speed of transition by NUTS2 region



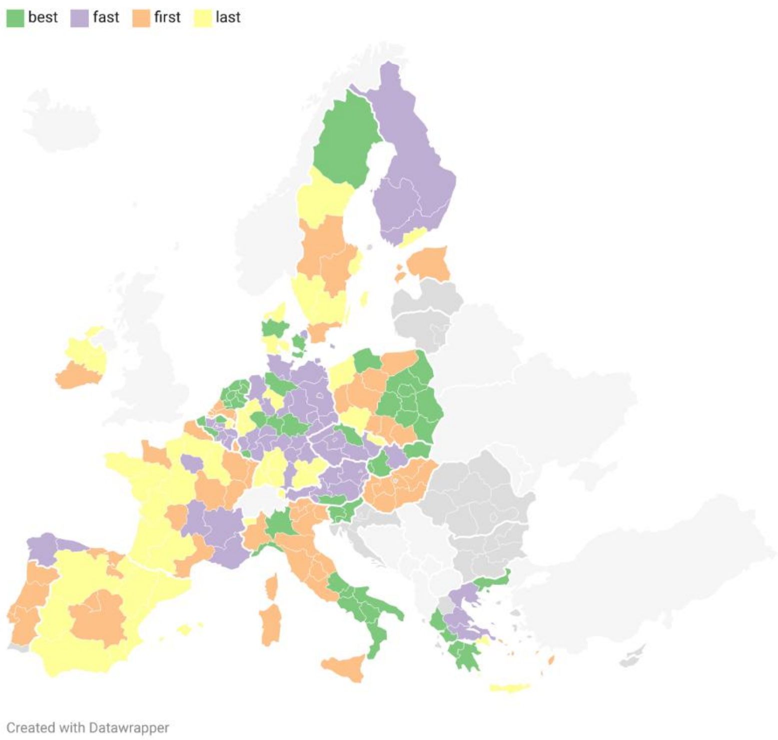
Panel (b): Level and speed of transition by NUTS2 region, by country



Source: authors

Note: The horizontal axis measures the slope (*b*) of the function (i.e. the sharpness of the regions' transition path), while the vertical axis measures the *integral* of the curve (i.e., the overall "level" of sustaina ble transition performance over time) for each NUTS2 region. In Pane l (b), both axes measure the country average of the slope (*b*) and the *integral*, while the size of the bubbles is proportional to the standard deviation of the slope *b* by country. Observe that Estonia and Luxem bourg have only one region.

Figure 3. Map of movers' profiles



Source: authors

Figure 3 shows no clear national-level patterns, with different transition profiles coexisting within the same country. A Moran's I test, performed both on the speed and the level, indicate the presence of spatial autocorrelation, suggesting that spatial spillovers and concentration effects are important, although not fully captured by our analysis. Overall, our elaborations provide insight into the dynamics of convergence around the green transition paradigm, even within member states, and show that the relationship between the speed of transition and the overall level support the path dependence hypothesis.

Looking at the variability of the transition speed within each state, Figure 2(b) also shows that some countries with, on average, a high level of transition (Portugal and Hungary) do not experience a particularly steep dynamic overall and are characterised by relatively low within country variability, while others (e.g., Austria, Italy, Poland and the Netherlands) harbour substantial regional differences in the acceleration towards sustainable development.

5. Concluding remarks

Our study highlights the uneven distribution of benefits in the EU's green transition, with regions exhibiting varying speeds and levels of sustainability performance. National environmental protection policies play a significant role, but regional disparities persist, and different stages of transition coexist within the same country. This evidence emphasizes the need for green transition strategies that consider the implications in terms of regional cohesion. Our findings encourage to reconsider traditional regional development criteria. While economic performance still has a critical role on transition capacity, it also leaves room for other dimensions of development, such as innovation, environmental protection and social cohesion. Further attention should be dedicated to identifying such aspects and systematically account for their complexity and multidimensionality. Future research should also examine the effectiveness of policy interventions in achieving a just and inclusive development, while advancing methodologies for analysing complex, multidimensional datasets. Empirical work based on collections such as ours can help spread evidence-based policymaking when addressing the multi-dimensional challenges of sustainability. This is a crucial task to undertake: while we demonstrate that the regional level is worth careful consideration, we also remark a difficulty in retrieving systematic data collections at the regional level. Alternative data sources, including geo-referenced data, can be valuable allies in this sense. From a methodological standpoint, we advocate for a deeper exploration of multivariate analysis approaches. The vast amount of information available today requires appropriate tools. These may help reveal hidden patterns that traditional economic theory might overlook, offering robust ground for policy design.

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References

Balland, P.A., Boschma, R., Crespo, J. and Rigby, D.L. (2019) Smart specialization policy in the European Union: relatedness, knowledge complexity and regional diversification, *Regional Studies*, 53(9), 1252-1268.

Cappelli, C., Costantini, V. and Consoli, D. (2021) The trap of climate change-induced “natural” disasters and inequality, *Global Environmental Change*, 70, 102329.

Castellani, D., Marin, G., Montresor, S. and Zanfei, A. (2022) Greenfield foreign direct investments and regional environmental technologies, *Research Policy*, 51(1), 104405.

Castellanos, J. and Heutel, G. (2021) *Unemployment, labor mobility, and climate policy*, Technical Report 25797, NBER.

Cepni, O., Guney, I.E. and Swanson, N.R. (2019) Nowcasting and forecasting GDP in emerging markets using global financial and macroeconomic diffusion indexes, *International Journal of Forecasting*, 35(2), 555–572.

Coppi, R. and Zannella, F. (1978) *L'analisi fattoriale di una serie temporale multipla relativa allo stesso insieme di unità statistiche,* XXIX Riunione Scientifica della SIS, Bologna.

Costantini, V., Crespi, F. and Paglialunga, E. (2018) The employment impact of private and publicactions for energy efficiency: evidence from European industries, *Energy Policy*, 119, 250–267.

European Commission (2018) *A clean planet for all: A European strategic long-term vision for a prosperous, modern, competitive and climate neutral economy*, European Commission COM(2018)773.

Faiella, I. and Lavecchia, L. (2021) *Households' energy demand and the effects of carbon pricingin Italy*, Technical Report 614/2021, Bank of Italy.

Federici, A. and Mazzitelli, A. (2005) *Dynamic factor analysis with STATA*, in 2nd Italian Stata Users Group meeting, Milano (10-11).

Geweke, J. (1977) *The Dynamic Factor Analysis of Economic Time Series,* North-Holland, Amsterdam.

Jolliffe, I.T. (2002) *Principal component analysis for special types of data,* in Principal Component Analysis, Springer Series in Statistics, 338-372, Springer, New York.

Kaiser, H.F. (1960) The application of electronic computers to factor analysis, *Education al and Psychological Measurement,* 20(1), 141–151.

Marin, G. and Vona, F. (2019) Climate policies and skill-biased employment dynamics: Evidence from EU countries, *Journal of Environmental Economics and Management*, 98, 102253.

Markkanen, S. and Anger-K Raavi, A. (2019) Social impacts of climate change mitigation policies and their implications for inequality, *Climate Policy*, 19(7), 827–844.

Napolitano, L., Sbardella, A., Consoli, D., Barbieri, N. and Perruchas, F. (2022) Green innovation and income inequality: A complex system analysis, *Structural Change and Economic Dynamics*, 63, 224–240.

OECD (2012) *The jobs potential of a shift towards a low-carbon economy: Final report for the EU Commission*, DG Employment.

O'Sullivan, K., Golubchikov, O. and Mehmood, A. (2020) Uneven energy transitions: understanding continued energy peripheralization in rural communities, *Energy Policy*, 138, 111288.

Oueslati, W., Zipperer, V., Rousselière, D. and Dimitropoulos, A. (2017) Energy taxes, reforms and income inequality: An empirical cross-country analysis, *International Economics*, 150, 80–95.

Paglialunga, E., Coveri, A. and Zanfei, A. (2022) Climate change and within-country inequality: New evidence from a global perspective, *World Development*, 159, 106030.

Purvis, B., Mao, Y. and Robinson, D. (2019) Three pillars of sustainability: in search of conceptual origins, *Sustainability Science*, 14, 681–695.

Qin, L., Aziz, G., Hussan, M.W., Qadeer, A. and Sarwar, S. (2024) Empirical evidence of fintech and green environment: using the green finance as a mediating variable, *International Review of Economics & Finance*, 89, 33–49.

Stock, J.H. and Watson, M.W. (2002) Macroeconomic forecasting using diffusion indexes, *Journal of Business & Economic Statistics*, 20(2), 147–162.

Vanli, T. (2024) Ranking of global smart cities using dynamic factor analysis, *Social Indicators Research*, 171(2), 405–437.

Vona, F. (2021) *Managing the distributional effects of environmental and climate policies: The narrow path for a triple dividend*, OECD Environment Working Papers No. 188, OECD, Paris.

Yenneti, K., Day, R. and Golubchikov, O. (2016) Spatial justice and the land politics of renewables: dispossessing vulnerable communities through solar energy mega-projects, *Geoforum*, 76, 90–99.

Zaman, B. and Borsky, S. (2021) The impact of supply structure on solar home system installations in rural off-grid areas, *Environmental Innovation and Societal Transitions*, 40, 625–644.