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More than just transition: Uncovering heterogeneous socio-economic outcomes of climate policies☆

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ABSTRACT

Achieving sustainability in sociotechnical systems requires transition processes supported by far-reaching policy action. By their very nature, these processes generate diverse and uneven consequences across territories, affecting key socio-economic dimensions such as unemployment, GDP, average disposable income, and the gender employment gap. Moreover, the web of linkages on which policy actions work eludes traditional analytical frameworks. Taking the European Union as a case study of a just transition process, we propose an empirical setting based on a machine learning technique with three main objectives. First, we develop a model that better captures the complexity of a sustainable and just transition process. Second, we compare results with standard quantitative assessment models, and we test whether the resulting insights derived from the implementation of ML-based approach align with economic theory. Third, we explore the potential of a controlled ML framework in supporting context-specific policymaking for a case study of a just and sustainable transition process.

1. Introduction

Achieving sustainable human systems requires more than incremental improvements; it demands transformative shifts to new socio-technical systems, i.e., sustainability transitions — a concept first explored by Elzen et al. (2004) and Grin et al. (2010). Such transitions are conceptualized as multidimensional, coevolutionary, and multi-actor processes (Köhler et al., 2019; Rosenbloom, 2025; Kortetmäki et al., 2025). The Just Transition framework (Newell and Mulvaney, 2013; Swilling, 2020), underscores the importance of pursuing these transformations in ways that ensure social acceptability and distributive justice, with particular attention to the spatial concentration of the benefits and burdens associated with the transition.

As a result, sustainability transitions research is called to answer 'big picture' questions, including how transitions affect inequality and which strategies can help mitigate their adverse social impacts (Sovacool et al., 2021). Yet, these questions introduce unprecedented layers of uncertainty and complexity that challenge conventional economic analysis. Stern and Stiglitz (2021) argue that traditional economic frameworks fail to represent faithfully a reality where multiple market failures are present. While valuable for outlining theoretical frameworks, traditional theoretical and empirical settings struggle to integrate heterogeneity and externalities effectively, limiting their normative capacity. These limitations stem from the inherently multidimensional nature of sustainability transitions, which involve complex interactions between economic, social, and environmental factors that traditional linear models cannot adequately capture. Effective policy-making can be conceptualized as a predictive task,

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whereby a nuanced understanding of macroeconomic trends and local dynamics informs actions toward achieving desired outcomes. However, developing a deep knowledge of all factors and potential impacts driving society is far from straightforward. The challenge lies in the complex web of interactions among multiple stakeholders and institutional layers, where policy actions generate cascading effects across interconnected systems. This complexity is particularly pronounced in sustainability policies which must simultaneously balance apparently contrasting elements such as economic prosperity, social equity, and environmental preservation (Purvis et al., 2019). Each of these dimensions introduces significant policy challenges, and their interconnectedness compounds the difficulty (Edmondson et al., 2019). Traditional economic models, with their reliance on simplified assumptions and linear relationships, are ill-equipped to handle this multidimensional complexity, creating a compelling case for alternative analytical approaches.

In addressing this gap, machine learning (ML) techniques offer a complementary analytical lens to the approaches traditionally used in sustainability transition studies. While existing research has relied on qualitative analyses, conceptual and multi-level frameworks, and formal modelling approaches (including system dynamics, agent-based models, and socio-technical simulations) to represent system-level change and the co-evolution of technologies, behaviours, and institutions (Holtz et al., 2015; Köhler et al., 2018; Papachristos, 2019), ML techniques offer promising ways of exploiting data abundance and variety to infer patterns of system-level change from observational data to draw predictions through an iterative learning process that mimics human decision-making (Kumar et al., 2024). This being the case, regional heterogeneity and, therefore, the spatial nature of the sustainability transition are not seen as an obstacle to overcome, but rather as the very source of data variation that makes the prediction possible.

The analysis is based on an original database matching together a diversified set of socio-economic variables at the regional (NUTS2) level for the European Union in the time frame 2000–2019. In this context, we develop an empirical analysis with three main objectives. First, we exploit ML techniques to construct a quantitative model designed to capture the complexity of the sustainable transition process. Second, by comparing results with standard quantitative assessment models, we test whether the resulting insights derived from the implementation of an ML-based empirical analysis align with economic theory. Finally, we assess whether a controlled ML framework could better support policy-making for a just and sustainable transition. This research direction is motivated by ML's demonstrated capacity for handling high-dimensional data and complex non-linear relationships — characteristics that align with the multifaceted nature of sustainability transitions. By leveraging ML's predictive capabilities, policymakers can better anticipate the socioeconomic outcomes of interventions, enabling more informed and effective policy design. Our approach explicitly harnesses the multidimensional analytical power of ML to provide a comprehensive framework for supporting sustainability transitions. The policy implications of our work are substantial. In line with the idea that all studies on sustainability transitions should admit that models are more relevant as 'learning machines' than as 'truth machines' (Turnheim and Nykvist, 2019), leveraging ML's capabilities allows not only to identify in advance the winners and losers of the sustainability transition, but also to learn which characteristics of a region make it more prone to experience losses. Insights like this are crucial to predict possible drawbacks at the regional level and to identify regions that may be subject to development lock-ins.

The rest of the paper is structured as follows. In Section 2 we frame the main contributions drawing the complexity of the concept of the just and sustainable transition. Section 3 provides a full description of the empirical framework adopted, including the database developed for the analysis (Section 3.1), the characteristics of the empirical method (Section 3.2), and the policy scenarios tested (Section 3.3). In Section 4 we discuss the main results. Section 5 concludes discussing the general policy implications of the existing driving factors and barriers qualifying a just and sustainable transition process.

2. Literature review

The link between sustainable transition and social justice is well documented in the literature. The interplay between sustainable transitions and social justice involves reconciling environmental goals with equity, inclusivity, and fairness in societal transformations. Indeed, a sustainable transition process in its core identity is mainly aimed at achieving environmental goals such as a deep decarbonization, resource efficiency or biodiversity protection, boosting ecological priorities on top of whatever strategy for economic growth. Such objectives may or may not have significant socio-economic and distributive consequences, where the outcome of the process could be significantly at risk if the negative impacts substantially affect the acceptability of the policies at play for such purpose (Avelino et al., 2024). If the society is particularly keen to a social justice perspective, in this case the policy-making process should also ensure that the sustainable transition is equitable, addressing the needs and rights of all stakeholders, particularly marginalized groups (Grossmann et al., 2022).

There are several aspects generated by the interaction between environmental protection goals and the related distributional impacts, with single or mutual causal relations and consequently different perspectives of analysis. 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. In this respect, the fiscal policies dedicated to support the adoption and diffusion of green energy technologies seem to be particulary effective in correcting negative distributional impacts of climate mitigation regulation (Costantini et al., 2025). This is in line with the more general findings that new technologies might contribute to address societal challenges and foster social welfare only if they are supported by well-designed public policies directed to ensure equity in individuals' well-being (Castellacci, 2023).

Additionally, a growing body of research is focusing on the non-linearity of the relation between environmental issues and income distribution, revealing that both channels are jointly working, with mutually self-reinforcing mechanisms at play. For example, there are several side effects associated to the development of new and sustainable technological trajectories, as the impact on the labour market through the creation of the so-called green jobs might also bring to negative effects to low-skilled workers (Consoli et al.,

2016; Napolitano et al., 2022). Environmental regulations can shift sector compositions, leading to (geographically concentrated) job creation or loss (Vona, 2021), with local labour 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 labour 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-K raavi (2019) frame the inequality-transition relationship within the broader context of climate change mitigation policies, emphasizing the importance of spatial analysis for understanding local labour market effects and regional disparities. O'Sullivan et al. (2020) further highlight the interrelation between spatial justice and energy justice in the context of energy system transformations. Knowledge and innovative capacity emerge as a pivotal factor in the so-called twin (i.e., green and digital) transitions (Damioli et al., 2024), but they are also unevenly distributed across regions (Balland et al., 2019).

From a global societal perspective, income distribution and climate change are closely interlinked since the most vulnerable groups (across and within countries) are disproportionately exposed to climate-related damages (despite being the ones who contribute least to climate change) and these impacts further erode their socio-economic resilience, deepening pre-existing inequalities (Cappelli et al., 2021; Paglialunga et al., 2022).

Overall, it emerges that from the one side, environmental stress is responsible for a significant increase in enlarging the divergence in income distribution. On the other side, those policies designed with the main intent of reducing the sources of environmental impacts (e.g., climate and energy policies or green innovation) might also produce a further pressure on more vulnerable groups.

From a political perspective, these drawbacks partly originate from the fact that environmental policies are often decided at the national level, even though local implementation may encounter different obstacles. This motivates adopting the European Union (EU) as a case study of an area where climate and energy policies are the core of the development strategy since decades, the policy objectives are decided at EU level of aggregation (supranational approach) while the practical decisions from a policy instruments perspective are taken at the national and regional levels. Indeed, the EU has progressively developed an integrated policy strategy that combines climate ambition, competitiveness, technological upgrading, and social inclusion, generating multiple channels through which local economic dynamics are shaped. The European Green Deal (EGD) sets the overarching framework for climate neutrality, with the primary aim of coupling GHG reduction with economic growth (European Commission, 2019). Complementary actions are directed at ensuring affordability and energy security (European Commission, 2025a), strengthening the competitiveness of both energy-intensive and clean-tech sectors, and expanding access to advanced technologies and innovative solutions, in a twin transition framework which emphasizes productivity gains through digital diffusion (European Commission, 2025b). These priorities are also reflected in the design of the NextGenerationEU and the Recovery and Resilience Plans, which allocate significant resources toward net-zero transition, digitalization, and industrial modernization (European Union, 2021b). Such intertwined transformations, in addition to decarbonization-innovation-growth measures, necessarily require also addressing employment risks and skills gap, in order to mitigate uneven distributional impacts across regions, sectors, and social groups. Given the heterogeneous socio-economic conditions at the sub-national level, the EU has also promotes mechanisms aimed at supporting social and territorial cohesion for a socially equitable transition. The Just Transition Mechanism (JTM),[1] for instance, operates through a place-based investment logic to assist the territories most exposed to transition pressures by supporting employment and re-skilling opportunities, and local diversification strategies (European Union, 2021a). In this vein, the strategy outlined during Von der Leyen's mandate follows the Keynesian idea that a "big push" in terms of environmentally virtuous public investments could lead the EU to an economic renaissance. Nonetheless, the specific policy instruments embedded in the EGD are not always designed (or effectively enacted) to properly respect a social justice criterion (Crespy and Munta, 2023), suggesting that some adjusting mechanisms are strongly required to reduce the negative impacts perceived by citizens.

Overall, as suggested by Vona (2023), green strategies such as the European one are designed to address three types of market failures: (i) negative environmental externalities; (ii) knowledge externalities that can be internalized in the green economy; (iii) network externalities inherent to green technologies. This brings about the compulsory requirement of a multidimensional approach that should integrate fairness in resource allocation, participatory governance, cultural recognition, and inter-generational responsibility. Only by addressing these aspects, it is possible to ensure that the transition process is not only environmentally sustainable but also socially inclusive, creating a more just and resilient society. Accordingly, in order to sustain the policy making process a complexity perspective must be adopted (van Bommel and Höffken, 2023), standard methods of analysis based on linear models might be able to capture only a portion of the web of causal relations and should be at least complemented by more flexible analytical solutions such as the machine learning techniques. This avenue is gaining momentum (Donti and Kolter, 2021; Yao et al., 2023; Biancalani et al., 2024).

3. Empirical framework

This section describes the dataset and the methodology used to investigate the complex dynamics of sustainable transitions in the EU. The analysis aims to contribute in bridging the gap between economic and policy perspectives by leveraging machine learning (ML) techniques to explore the intricate relationships between socio-economic, environmental, and innovation factors. By integrating

[1] And the new Just Transition Fund (JTF) introduced in the 2021–2027 period within the Cohesion Policy framework.

regional-level (NUTS 2) data from 2000 to 2019, we seek to capture the nuanced interactions shaping regional disparities and their implications for sustainability transitions.

Building on the EU policy context outlined above, we analyse how regions respond to changes related to decarbonization, innovation, and labour-market adjustments, which represent core dimensions of the EU's policy framework. The dataset used in the analysis includes a comprehensive array of indicators across socio-economic, environmental, and innovation dimensions. This allows us to simulate outcomes of alternative policy interventions and study regional disparities and the potential distributional consequences across the three pillars of sustainability.

The empirical ML framework allows us to develop a quantitative model that captures the complexity and interdependencies inherent in sustainable transition processes. This approach forms the basis for a robust analysis of policy trade-offs and synergies, providing valuable insights to support equitable and effective sustainability transitions.

3.1. Data

Our dataset incorporates regional data for EU NUTS 2 regions, supplemented with national data on policy settings, over a 20-year time frame (2000 to 2019). The dataset includes 38 variables, mirroring the three-pillar structure in Purvis et al. (2019) (see Table 1 for a detail of variables' sources and codification in our dataset).[2]

Our scenarios will be evaluated on four socioeconomic indicators. First, the regional unemployment rate, expressed as a percentage of the labour force. Because employment was at the core of the Cohesion policy planning 2014–2020 (thematic objective 8, see European Commission (2023)), this dimension has strategic policy implications. Unemployment rates have been widely used to measure the societal impacts of socio-technical transitions (Castellanos and Heutel, 2021; Vona, 2021). Secondly, we look at Gross Domestic Product (GDP) in NUTS 2 regions, measured in constant million euros, in line with studies that see economic growth as a substantial outcome to determine disparities in green transition deployment, and development traps along climate policies (Iammarino et al., 2019; Diemer et al., 2022). Third, and complementarily, we consider disposable income in NUTS 2 regions, measured in million purchasing power standards.[3] Disposable income is more directly linked to households' consumption behaviour and it is therefore used to explore uneven household effects of climate policies (Rodríguez-Pose and Bartalucci, 2023). Finally, we explore the effect on the gender employment gap by NUTS 2 regions (as a percentage). This serves as a proxy for intersectionality and inclusivity in socio-economic systems and aligns with extensive literature that uses gender as a proxy for systemic inclusivity (see Johnson et al. (2020) for a review). Gender representation in climate governance is crucial for ensuring equitable transitions (Kronsell, 2013). Evidence suggests that women are significantly underrepresented in both carbon-intensive sectors and in high-technology or (green) innovation-driven sectors (Maldonado et al., 2024). This structural segmentation of the labour market adds further nuances and helps explain why shock to innovation and/or sectoral restructuring may not see corresponding improvements in gender equality.

The features considered for the prediction task are inspired by the literature review in Section 2. Patenting activity is a common proxy for the innovative capacity of a territory (Barbieri et al., 2023). Similarly, eco-patents capture eco-innovative propensity, often linked in literature to successful green transitions (Costantini et al., 2017, 2018; Napolitano et al., 2022). The OECD REGPAT (Regional Patent) Database collects information on patent applications at the European Patent Office (EPO) as well as within the Patent Cooperation Treaty (PCT). Only the first case is considered in our analysis. We use the Spring 2023 version of the dataset and focus on EPO applications. From the database, we extract information on the technological class of patents by cooperative patent classification codes (CPC). We then assign patent applications to each NUTS 2 region, counting how many have priority year between 2000 and 2019 by an inventor located in the region. This step is then 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. Fig. 1 presents an overview of the results of our counting.[4]

However, patenting activity alone may not capture the full extent of the innovative landscape in regions. Following the understanding that regional support for R&D plays a crucial role in preparedness against climate change and complex societal changes (Cappellano et al., 2024), we include variables of knowledge capital building as collected in the Regional Innovation Scoreboard (RIS). The RIS database focuses on research and innovation-related metrics. Out of those available, we select three variables: employment in technology and knowledge-intensive sectors, participation rate in education and training, and tertiary educational attainment in the age group 25–64. The latter two come as percentages, while the former is expressed in thousands of persons, therefore we transform it in relative terms by dividing the absolute value by the yearly regional population.

Moreover, we consider relative employment in sectors vulnerable to climate transition (hereafter "vulnerable sectors"). Vona (2021), Vandeplas et al. (2022), Rodríguez-Pose and Bartalucci (2023) identify reliance on labour in "brown" sectors as a key

[2] To preserve as much information as possible, breaks in time series are interpolated. Observations for region i at time t that still present missing values for certain variables are dropped.

[3] Both GDP and disposable income are considered in per capita terms, i.e. we divide the absolute value by the yearly regional population

[4] Due to mismatches between OECD regional classifications and Eurostat, and to NUTS 2 updates over the time frame considered, some recoding was necessary. Find details on the process in the Annex.

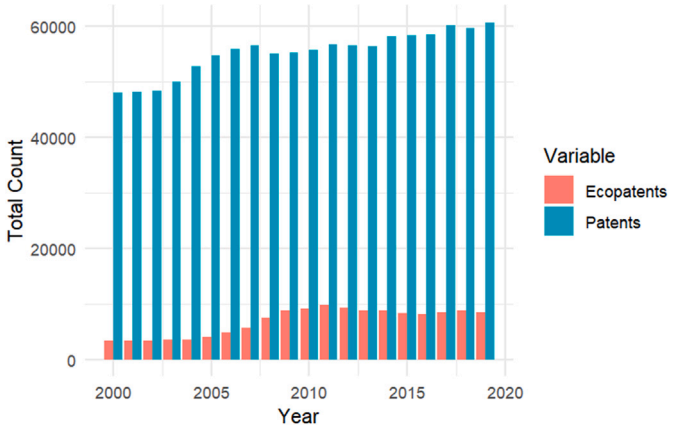

Fig. 1. Number of patent applications in the EU, by year.

determinant of regional vulnerability to the distributive effects of climate policies. To incorporate this research strand, we include employment data by economic activity for NUTS 2 regions across NACE sectors A through F, measured in thousands of persons.[5]

We complement information on sectoral employment and innovation dynamics by including the median age of the population in the region, to control for the possible relevance of demographic dynamics.

Greenhouse gas emissions are a common indicator of the environmental footprint of human activities. Even if they are not exhaustive of the overall impact, these are widely used to assess the extent and success of green transitions and, more broadly, sustainable development (Bianchini et al., 2023). The EDGAR (Emissions Database for Global Atmospheric Research) collects emission data from different sources, and harmonizes this information to generate detailed estimates of emissions for a wide range of pollutants. The measurements available for the NUTS 2 level, that we include in our dataset, are carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), and fluorinated greenhouse gases (F-gases), expressed in Kt of CO2eq. For these variables, we consider a per capita value by dividing each variable by the yearly value of the regional population.

Lastly, the OECD environmental policy stringency (EPS) indicators offer insights into countries' regulatory landscape surrounding environmental protection and sustainability. These indicators gauge a country's efforts to mitigate pollution and foster sustainable development practices. We assign to every region the corresponding national score. This composite index tracks climate change and air pollution mitigation policies. Increased stringency, indicative of favourable institutional and political landscapes, is a strong predictor of environmental performance (Frohm et al., 2023) and eco-innovation (Ghisetti and Pontoni, 2015; Xie et al., 2023). We assign to every region the corresponding national score.[6]

3.2. Elastic net model for spatial regression

ML is a bundle of techniques to detect patterns hidden in complex data structures, using an iterative process, called cross-validation. Cross-validation is a statistical method used to evaluate the performance of a model by testing it on data that were not used during the training phase. The process involves splitting the dataset into multiple subsets, or "folds"; the model is trained on some of these folds (the training set) and validated on the remaining fold(s) (the validation set). This process is repeated several times, with each fold taking a turn as the validation set. The performance of the model (or "fit") is evaluated on different measures of the error between predicted and observed values in the validation step.[7]

[5] Our classification of vulnerable sectors represents a calibration between data availability and existing literature on sectors most likely to be significantly affected by sustainable transition. Following (Rodríguez-Pose and Bartalucci, 2023), brown sectors typically include agriculture, forestry, and fishing (A); mining and quarrying (B); specific manufacturing subsectors such as coke and refined petroleum products (C19), chemicals (C20), non-metallic mineral products (C23), and basic metals (C24); utilities including electricity, water supply, and waste management (D, E); and transport (H). However, we make several adjustments to this framework. First, we exclude transport sector H due to its aggregation with sectors G and I in Eurostat data. Second, unlike (Rodríguez-Pose and Bartalucci, 2023), we retain the entirety of NACE sector C (manufacturing). Third, we include construction (NACE F), given evidence from Maldonado et al. (2024) that this sector is particularly prone to transformation due to high future demand for green jobs and in light of recent discussions to include the construction sector within the Emission Trading Scheme framework.

[6] The index includes scores for categories such as CO2 ETS, CO2 tax, diesel regulations, energy policies, and renewable energy initiatives, among others.

[7] To evaluate the performance of our models, we rely on common error metrics widely used for regression tasks, like in Caravaggio and Resce (2023): Root Mean Squared Error (RMSE), Standardized RMSE, the Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). RMSE measures the square root of the average squared differences between the observed and predicted values. To allow comparability across different datasets, the standardized RMSE normalizes RMSE by the standard deviation of the observed errors. In the same spirit, MAE calculates the average absolute error, while the MAPE expresses the MAE as a percentage of the actual values. It is commonly used for its interpretability, in cases where a continuous variable is predicted.

Table 1
List of Variables.

Name	Description	Unit of Measure
Source: Cohesion Open Data Platform		
coh	Cohesion fund recipient	1 = yes, 0 = no
Source: EDGAR		
ch4	Methane emissions	Kt CO_2eq
co2	Carbon dioxide emissions	Kt CO_2eq
fgas	Fluorinated gases emissions	Kt CO_2eq
n2o	Nitrous oxide emissions	Kt CO_2eq
Source: EPS		
c_co2ets	CO_2 Trading Scheme	Integer
c_co2tax	Carbon dioxide (CO_2) Tax	Integer
c_diesel	Diesel tax	Integer
c_enepol	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_solar	Solar Energy support (Auctions & FITs)	Integer
c_sox	Emission limit value SOx	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
Source: Eurostat		
disp	Disposable income	Million purchasing power standards
egap	Gender employment gap	Percentage
emp	Employment in NUTS2 regions	Thousands of persons
gdp	Gross domestic product (GDP)	Million euros
htec	Employment in technology and knowledge-intensive sectors	Thousands of persons
lllearn	Participation rate in education and training	Percentage
median	Median age of the population	Years
nacea	Employment in Agriculture, forestry and fishing	Thousands of persons
nacebe	Employment in Industry (except construction)	Thousands of persons
nacef	Employment in Construction	Thousands of persons
pop	Population by NUTS 2 regions	Thousands of persons
ted	Tertiary educational attainment, age group 25–64	Percentage
unemp	Unemployment rate	Percentage
Source: Own elaboration on REGPAT data		
ecopat_count	Number of eco-innovative patent applications (EPO)	Integer
pat_count	Number of patent applications (EPO)	Integer
Source: Own elaboration on Eurostat data		
vuln	Employment in vulnerable sectors (NACE A to F)	Thousands of persons

Note: All variables, except those from the EPS dataset (which are at the country level), are at the NUTS 2 level. Employment data by economic activity follow NACE Rev. 2. For consistency, in the EN model we convert all absolute values to relative measures using two approaches: (1) dividing the variable by regional population, or (2) dividing by the total number of employed persons in the region, in the case of sectoral employment variables. Variables that undergo this transformation will be marked with the suffix "*_rel*".

Unlike traditional statistical methods, which rely on predefined assumptions and equations describing relationships between variables, ML models derive predictions based on observed trends and interrelations, in an assumption-light way, letting the algorithm formulate and develop hypotheses as cross-validation moves forward.

In our case, we structure the prediction task as predicting different response variables, at the regional level, for the last year of our panel. We perform the training stage by regressing the $Y_{i,t}$, on all the features in our dataset $features_{i,t}$, for all t except the last. In addition, we include among the regressors a spatial adjacency matrix W to account for agglomeration and geographical spillovers. W has value of 1 when two regions are neighbours and 0 otherwise. The out-of-sample prediction is performed in the last year.

$$Y_{i,t} = f(features_{i,t}, W) \tag{1}$$

Y is alternatively one of four socio-economic variables (see par 4.2). $f(.)$ is the best-fitted Elastic Net (EN) model ((Tibshirani, 1996); Zou and Hastie (2005); Taylor and Tibshirani (2015)). The Elastic Net solves the following optimization problem:

$$\hat{\beta} = \arg\min_{\beta} \left(\frac{1}{2n} \sum_{i=1}^{n} \left(y_i - \mathbf{x}_i^\top \beta \right)^2 + \lambda \left(\alpha \|\beta\|_1 + \frac{1-\alpha}{2} \|\beta\|_2^2 \right) \right) \tag{2}$$

Here:

- y_i and $\mathbf{x}_i$ are the observed response and predictor vector for the ith observation, respectively.
- $\|\beta\|_1 = \sum_{j=1}^{p} |\beta_j|$ is the LASSO penalty.
- $\|\beta\|_2^2 = \sum_{j=1}^{p} \beta_j^2$ is the Ridge penalty.
- $\lambda > 0$ controls the overall regularization strength, while $\alpha \in [0, 1]$ determines the balance between LASSO and Ridge penalties.

The L1 penalty ($\|\beta\|_1$) encourages sparsity by shrinking some coefficients exactly to zero, effectively performing feature selection. In contrast, the L2 penalty ($\|\beta\|_2^2$) distributes shrinkage more evenly across coefficients, favouring models that handle correlated predictors more effectively. By blending these approaches, Elastic Net inherits the advantages of both methods, balancing variable selection and stability in regression estimates. The Elastic Net is particularly valuable in high-dimensional settings, where traditional regression methods struggle due to multicollinearity or the curse of dimensionality.

3.3. Scenarios

Once we retrieve the optimal model, we use it to predict four scenarios. Three of these reflect the key EU policy domains shaping the sustainability transition: decarbonization efforts at the core of the European Green Deal, competitiveness and innovation upgrading central to the twin transition and the Recovery and Resilience Plans, and labour-market restructuring supported by cohesion mechanisms such as the Just Transition Instrument. The fourth is a policy-mix scenario that reflects their combined operation in EU practice. More specifically:

Scenario 1 — Enhanced innovative capacity

Grillitsch and Hansen (2019), argue that a pre-existing industrial capability is a condition for the development of local green economies. The innovative activity of firms mediates the relationship, as confirmed by Perruchas et al. (2020) and Barbieri et al. (2023). This scenario simulates uniform growth in patent applications across all regions, calibrated to match the average growth rate observed in regions not receiving cohesion funds during 2000–2018.[8] The objective is to assess how a sustained enhancement in innovative capacity — known to be strongly associated with the green transition — might influence the socioeconomic performance of regions.

Scenario 2 — Emissions cap

The Fit for 55 Package establishes a target of reducing greenhouse gas (GHG) emissions by 55% by 2030, relative to 1990 levels. To simulate this scenario, we use total GHG emissions data for NUTS2 regions in 1990 from the EDGAR database. We constrain 2019 emission levels to represent a 55% reduction relative to their 1990 baseline values, and simulate a scenario where GHG emissions decline at the average yearly rate necessary to achieve this target.

Scenario 3 — Labour market policies

Vandeplas et al. (2022) find a positive and significant correlation between employment in vulnerable sectors and unemployment, at the NUTS 2 regional level. At the same time, Rodríguez-Pose and Bartalucci (2023) argue that regions reliant on brown energy generation and consumption are experiencing the harshest consequences of green policies. The Clean Planet for All initiative in 2018 foresaw particular backlash on the energy and industrial sectors. This scenario simulates a uniform reduction in employment in vulnerable sectors, calibrated to match the average rate observed in regions not receiving cohesion funds during 2000–2018.

Scenario 4 — Policy mix

Rosenbloom (2017), Turnheim and Nykvist (2019) point out that sustainability transitions consist of a broad range of economic, technological, and behavioural changes that are often overlapping. In sum, in a real-life context, the three scenarios above could as well co-exist. To address this possibility, we construct a "policy mix" scenario, where the previous three are combined.

The parameters for the simulations are carefully chosen following an in-depth analysis of historical trends to avoid the trap of extreme counterfactuals (King and Zeng, 2006). Additionally, the evolutions we simulate are within the historical trends exposed in Table 2.

For each of the three scenarios, we evaluate the effects of variations of certain features on the four response variables: unemployment, GDP, disposable income, and gender employment gap. Our choice of unemployment as the primary dependent variable in the prediction task aligns with a vast body of literature that sees unemployment as a crucial indicator of the acceptability of green policies at the local level (Vona, 2023). In this strand of literature, unemployment is regarded as a proxy for social cohesion and well-being, two of the three pillars of sustainable development (Purvis et al., 2019). Moreover, we also account for GDP, disposable income, and the gender employment gap as response variables, as they provide complementary insights into economic performance, household welfare, and labour market inclusivity, all of which are critical dimensions of sustainable development.

[8] We acknowledge that patent data do not capture the full scope of the regional system of innovation. Nonetheless, patent statistics constitute a consistent and regionally comparable indicator of local inventive capacity, and are widely employed as a consistent proxy in empirical analyses. In addition, while patents are the primary outcome considered, the dataset (and thus the model) also includes additional indicators to provide a broader representation of local innovation systems.

Table 2
Parameters chosen for the scenarios. Note: The table reports the average yearly percentage variation and standard deviation observed in more advanced regions.

Variable	Average yearly growth (%)	SD
Number of patent applications	3.06	0.47
Employment in vulnerable sectors	−0.77	0.06

4. Results

4.1. Descriptive statistics and baseline econometric results

As a preliminary step in the empirical analysis, we explore the correlations between key variables with the aim of examining the patterns emerging both within and across groups of variables, namely, economic performance indicators, social factors, emissions, innovation, and environmental policy measures. The results, presented in the heatmap in Fig. 2, reveal that variables capturing economic performance, such as GDP and disposable income, are positively correlated. On the other hand, and consistent with expectations, unemployment shows a negative correlation with both GDP and disposable income. Moreover, the gender employment gap is positively correlated with unemployment, suggesting that regions with higher unemployment also tend to exhibit greater disparities between men and women in labour market participation. Innovation variables, including general patents and eco-innovation, are positively correlated with GDP and disposable income, highlighting the role of technological development in driving economic performance.

Turning to indicators related to the labour market, the correlation map shows a positive relationship between employment in knowledge-intensive sectors and educational attainment. Conversely, unemployment is negatively correlated with educational attainment. Taken together, this evidence suggests the crucial role of education in facilitating access to the labour market and, in particular, to skilled labour opportunities.

In the environmental dimension, we observe strong positive correlations among variables representing GHG emissions (e.g., CO2, methane, and nitrous oxide), indicating that regions with high emissions of one pollutant often exhibit elevated levels also of others. Similarly, Environmental Policy Stringency (EPS) measures (e.g., CO2 taxes and CO2 trading schemes) display strong positive within-group correlations, reflecting the tendency of regions with high environmental commitments to adopt multiple complementary policies. Notably, the heatmap also shows negative correlations between EPS measures and emissions, indicating that regions in countries with more stringent environmental policies tend to have lower levels of emissions, which points to a degree of environmental policy effectiveness.

These observed patterns highlight the importance of considering interdependencies among variables, particularly in policy analysis. Measures targeting one variable or group of variables are likely to have indirect effects on others, reinforcing the need for an integrated approach to policy design that accounts for these complex relationships, both to enhance the effectiveness of the policies and to avoid unintended consequences across economic, social, and environmental dimensions.

This evidence is also corroborated by the results from the econometric exercise reported in Table 3, although the interpretation is different, and some nuances emerge. More specifically, Table 3 provides the results obtained from Ordinary least Square (OLS) econometric estimations, where we test the determinants of our four response variable of interest, i.e., (from column 1 to 4) unemployment, GDP, disposable income, and gender employment gap. In all models we include regional (NUTS 2) and year fixed effects to control for time-invariant characteristics of regions and common time trends. We also perform all estimates clustering the standard errors at the regional NUTS 2 level to control for heteroskedasticity and autocorrelation.

The results in Column 1 show that GDP is negatively associated with unemployment levels, suggesting that relatively wealthier regions tend to have lower unemployment rates. CO2 emissions also have a negative and statistically significant association with unemployment, implying that, everything else being equal, higher emissions levels are linked to higher employment levels. Innovation, as measured by EPO patents, exhibits a positive and statistically significant coefficient, potentially pointing to a trade-off between innovation performances and job creation. While the coefficients for median age, education participation, and both market-based and non-market-based EPS measures are statistically significant, their magnitudes are negligible.

In Column 2, participation in education and training, and patent activity are both positively associated with GDP, highlighting the key role of innovation and human capital in driving economic growth. Conversely, unemployment, median age, and EPS measures show negative and statistically significant coefficients, suggesting a detrimental influence of these factors on economic performance.

For average disposable income (Column 3), most results align with those for GDP. Specifically, unemployment, median age, and non-market-based EPS measures have significant negative effects, while the variable *lllearn* has a positive and significant association, supporting the idea that higher involvement in education and training fosters income growth. However, differently from the previous results, EPO patents negatively affect disposable income, while CO2 emissions show a positive and significant coefficient. These findings align with the evidence in Column 1: higher emissions levels, which are associated with increased employment, also contribute to higher disposable income. On the other hand, the trade-off between innovation and job creation may also lead to a negative effect on average income, reflecting potential disparities in income distribution.

Finally, Column 4 focuses on the gender employment gap, identifying two significant predictors: the unemployment rate and employment levels in technology and knowledge-intensive sectors. Both coefficients are positive and, while the magnitude of the latter is nearly zero, the former indicates that higher unemployment exacerbates gender disparities in the labour market.

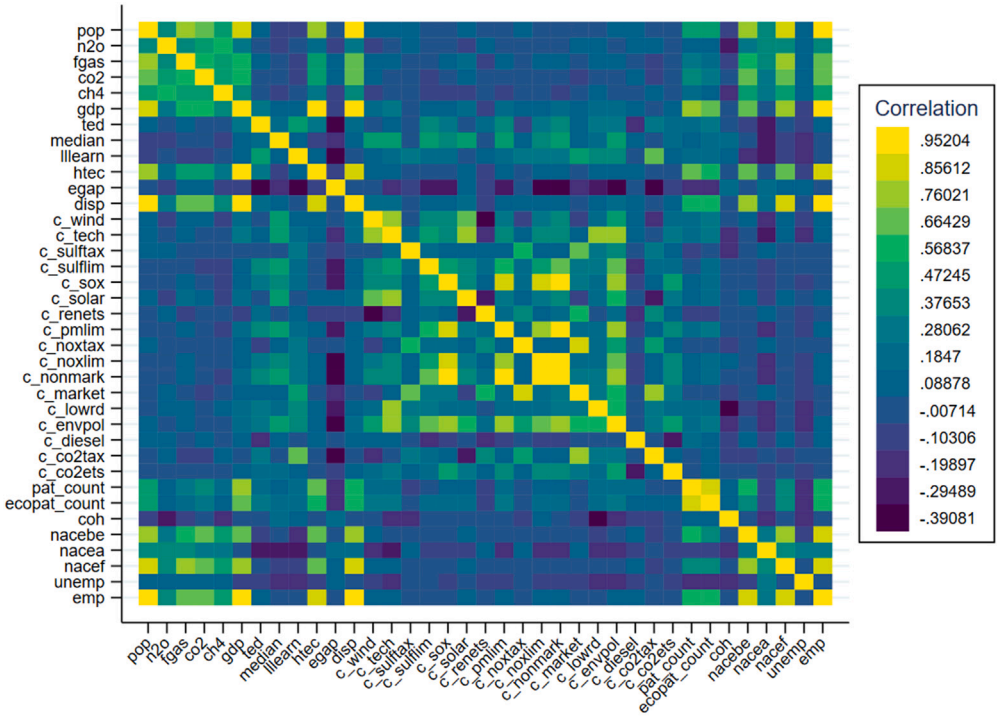

Fig. 2. Heatplot of Correlation Between Variables in the Dataset.

This evidence highlights the complex interplay between economic, social, and environmental factors, revealing trade-offs and synergies that policymakers should take into account to jointly foster inclusive growth, advance technological systems, environmental sustainability and equitable development. An additional point in this regard concerns the limited predictive power of the country-level EPS indicator. Uniform national environmental policies can generate heterogeneous — and in some cases contrasting — effects across regions due to differences in industrial structures, labour-market compositions, and local institutional capacities. In such cases, a coefficient close to zero may simply reflect the averaging of divergent region-specific responses, where some regions experience positive effects and others negative ones. This pattern of limited predictive capacity of national-level indicators in explaining regional variation further supports the use of ML techniques, which are particularly well suited to capture non-linearities, context-specific responses, and complex interaction patterns that traditional linear models may overlook.

4.2. ML model performance and feature importance

The results in Table 3, while informative as a baseline, are likely inflated by multicollinearity among predictors, resulting in unstable and unreliable coefficients. In contrast, the Elastic Net method incorporates L1 and L2 penalties, performing feature selection and coefficient shrinkage to filter out redundant or irrelevant information. This approach results in more robust and interpretable coefficients, effectively clearing out the "noise" that complicates causal inference. Although Elastic Net sacrifices a direct claim to causality, its advantages in improving model stability and interpretability outweigh this trade-off for the scope of our analysis.

The results, illustrated in Figs. 3 to 6, highlight the importance of different variables in predicting, respectively, unemployment, GDP, average disposable income, and the gender employment gap at the regional level, as identified by the EN model. The performance of the fitted models is in Table 4.

Fig. 3 shows that, aside from the regional the employment rate (*emp*), the most influential feature explaining unemployment is its spatial lag (*spatial_lag_unemp*), i.e., the unemployment levels registered in neighbouring regions, highlighting that proximity and concentration effects have a key role in shaping local labour market outcomes. EPS indicators show notable relevance, although with different signs. While some indicators, like the renewable energy trading scheme (*c_renets*), the public R&D expenditure in low carbon technologies (*c_lowrd*), the tax on sulphur oxides (*c_sulfax*), and wind energy support policies(*c_wind*) show a negative link with unemployment, other indicators go in the opposite direction. Overall, these results support the hypothesis that national environmental protection strategies play a crucial role in shaping local unemployment patterns. However, the impact of each specific measure seems widely heterogeneous, warranting further research. Participation in lifelong learning (*lllearn*) and tertiary education attainment (*ted*), in percentage, are associated with higher unemployment rates. Coupled with the negative sign of *median*, we can interpret this finding as an indication that demographically older regions tend to show higher unemployment, requiring

Table 3
OLS regression model with regional and year fixed effects.

	(1) Unemployment	(2) GDP	(3) Avg. disp. income	(4) Gender empl. gap
GDP	−0.00133***			0.00009
	(0.00022)			(0.00013)
Unemployment		−33.14539***	−43.57921***	0.04985**
		(5.88857)	(6.03629)	(0.01839)
Median age	−0.00000***	−0.00103***	−0.00101***	0.00000
	(0.00000)	(0.00008)	(0.00012)	(0.00000)
lllearn	0.00000***	0.00011***	0.00008*	−0.00000
	(0.00000)	(0.00002)	(0.00003)	(0.00000)
htec	−0.00000	0.00001	−0.00001	0.00000***
	(0.00000)	(0.00001)	(0.00001)	(0.00000)
CO2 emissions	−0.00379***	0.04963	0.41385***	0.00031
	(0.00035)	(0.06910)	(0.06570)	(0.00022)
Patent (EPO)	0.04429***	5.53345***	−7.76134**	0.00604
	(0.00641)	(1.48728)	(2.46167)	(0.00555)
EPS market	−0.00001***	−0.00150***	−0.00016	0.00000
	(0.00000)	(0.00013)	(0.00021)	(0.00000)
EPS non-market	0.00000***	−0.00118***	−0.00156***	−0.00000
	(0.00000)	(0.00009)	(0.00017)	(0.00000)
N	4160	4160	4160	4160
adj. R^2	0.666	0.953	0.973	0.662
NUTS 2 FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

* *t* statistics in parentheses. $p < 0.05$.
** *t* statistics in parentheses. $p < 0.01$.
*** *t* statistics in parentheses. $p < 0.001$.
lllearn is the Participation rate in education and training;
htec is the Employment in technology and knowledge-intensive sectors.

Table 4
Model performance across target variables.

	Unemployment	GDP	Disposable income	Gender employment gap
R^2	0.86853	0.78002	0.73820	0.55797
RMSE	1.90575	0.00732	0.00193	5.56332
Normalized RMSE	0.39969	0.48830	0.52652	0.96535
MAE	1.37613	0.00420	0.00150	4.17179
MAPE	0.29566	0.13772	0.09322	0.49441

Notes: Performance variables are computed on the test set.

reskilling programs to take place. Other key predictors include the share of employment in the construction sector (*nacef_rel*) and in vulnerable sectors (*vuln_rel*), suggesting a strong link between regional employment levels and sectoral composition. Interestingly, patent applications (*pat_count_rel*) show a relatively weaker direct influence of innovation-related variables on unemployment.

Similarly, for regional GDP (Fig. 4), the spatial lag (*spatial_lag_gdp*) — representing GDP in neighbouring regions — emerges as the most influential factor, further suggesting the spatially interconnected nature of regional economic activities. As it is to be expected, overall employment levels (*emp_rel*) serve as a key driver of regional GDP. Among sectoral employment variables, employment in the high-tech sector (*htec_rel*) positively affects regional GDP, while the opposite can be said of employment in the industrial sector (*nacebe_rel*) and in vulnerable sectors (*vuln_rel*). This contrasting effect reflects the importance of high-value-added employment in regional economies. The presence of tertiary education attainment (*ted*) and eco-innovative patents (*ecopat_count_rel*) among the top drivers, underscores the critical role of human capital and social factors in determining economic output. In contrast to unemployment, environmental regulation indicators from the EPS dataset play a less prominent role in explaining regional GDP variations, suggesting that environmental regulation may have more direct effects on labour market outcomes than on overall economic output. On the other hand, pro capita CO_2 emissions (*co2_rel*) are associated with higher GDP levels, indicating how economic performance comes at the price of a higher environmental footprint in most European regions.

Fig. 5 shows that the main predictor of regional average disposable income is its spatial lag (*spatial_lag_disp_rel*), suggesting once again that concentration effects are a substantial component of regional economic development and ought not to be overlooked. A higher disposable income is driven upwards by a higher employment rate and downwards by a higher share of employment in the industrial sector and the construction sector (*nacebe_rel* and *nacef_rel*). In this context, regions that are better equipped in terms of eco-innovative activities (*ecopat_count_rel*) have higher disposable income. Note that the same cannot be said of overall patenting activity (*pat_count_rel*). These results jointly reflect the importance of both labour market conditions and innovation activities. EPS indicators give a few interesting indications. We remark that emission limits (*c_noxlim* and *c_pmlim* generally point in the direction of a lower disposable income. The same applies for carbon tax (*c_co2tax*) and for solar energy support (*c_solar*). Conversely, expenditure

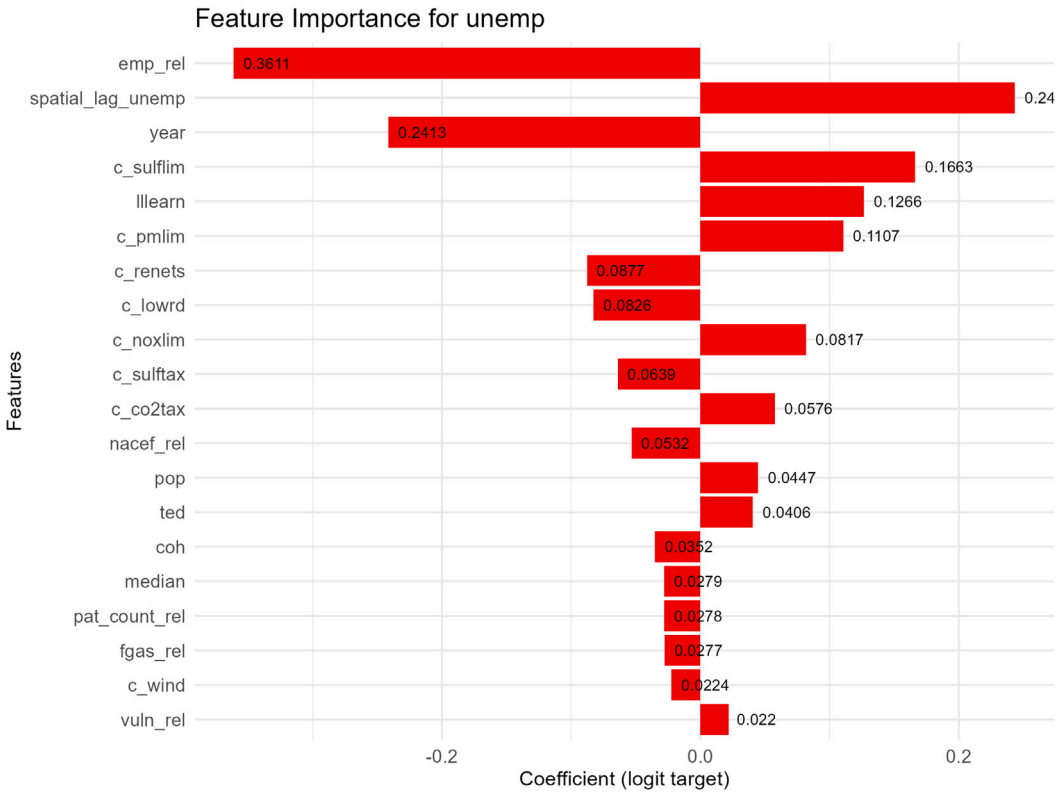

Fig. 3. Feature importance plot — Unemployment
Notes: Feature importance plot indicating the relative contribution of predictors to the fitted model. The intercept ranked highest but was omitted for readability. The dependent variable was logit-transformed to ensure EN predictions remain within the 0–100 range.

on low emission R&D (*c_lowrd*) and renewable energy trading systems (*c_renets*) point in the opposite direction. These contrasting effects, coupled with the role played by *ecopat_count_rel*, suggest that regions investing proactively in green transition capabilities — rather than merely complying with environmental restrictions — experience measurable economic benefits in terms of disposable income.

Finally, as for the gender employment gap (Fig. 6), the most important predictor is still the spatial lag *spatial_lag_egap* (i.e., the gender employment gap in neighbouring regions), suggesting that labour market characteristics are spatially concentrated, with pockets of EU areas where women are more persistently excluded from employment, both within their own region and in adjacent ones. The presence of employment variables (*nacef_rel*, *htech_rel*, and the aggregated vulnerable sectors *vuln_rel*), reinforces the idea that sectoral composition not only plays a critical role in influencing overall unemployment levels, but also shapes gender disparities in employment. Interestingly, three out of four GHG emissions rank among the main predictors. In particular, we note how nitrous oxide emissions (*n2o_rel*), and CO_2 emissions (*co2_rel*) show a positive correlation with the gender employment gap. This pattern suggests that women are not uniformly distributed across sectors vulnerable (or less vulnerable) to the sustainability transition, and that their lower/higher presence from certain industries may amplify gendered disparities in labour market outcomes.

Taken together, these results show that all models are strongly driven by spatial spillovers and employment levels across sectors. While innovation and education are critical drivers of long-term economic growth and welfare, their effects on employment levels may be more indirect, e.g., potentially mediated through industrial transformation and regional preparedness. Overall, the results suggest that regions are strongly influenced by the socio-economic and employment conditions of their neighbours, highlighting the spatially interconnected nature of these dynamics. In contrast, national-level environmental protection measures exhibit limited predictive power for regional outcomes. This finding suggests that, although national institutional capacity plays a role in determining socioeconomic outcomes, regional heterogeneity and spatial spillover effects are more decisive factors. Moreover, all the features we use to construct the scenarios consistently emerge among the most significant predictors. These empirical patterns provide robust validation for our analytical framework. First, they substantiate the theoretical justification for our variable selection in the shock scenarios. Second, they demonstrate that adopting a regional focus coupled with explicit modelling of spatial spillover effects yields substantially different insights compared to conventional regression approaches, while corroborating *a priori* theoretical expectations.

Finally, a comparative analysis of Figs. 3–6 and Table 3 reveals several noteworthy discrepancies that warrant examination in light of theoretical expectations. Regarding unemployment, patent applications demonstrate negligible predictive importance

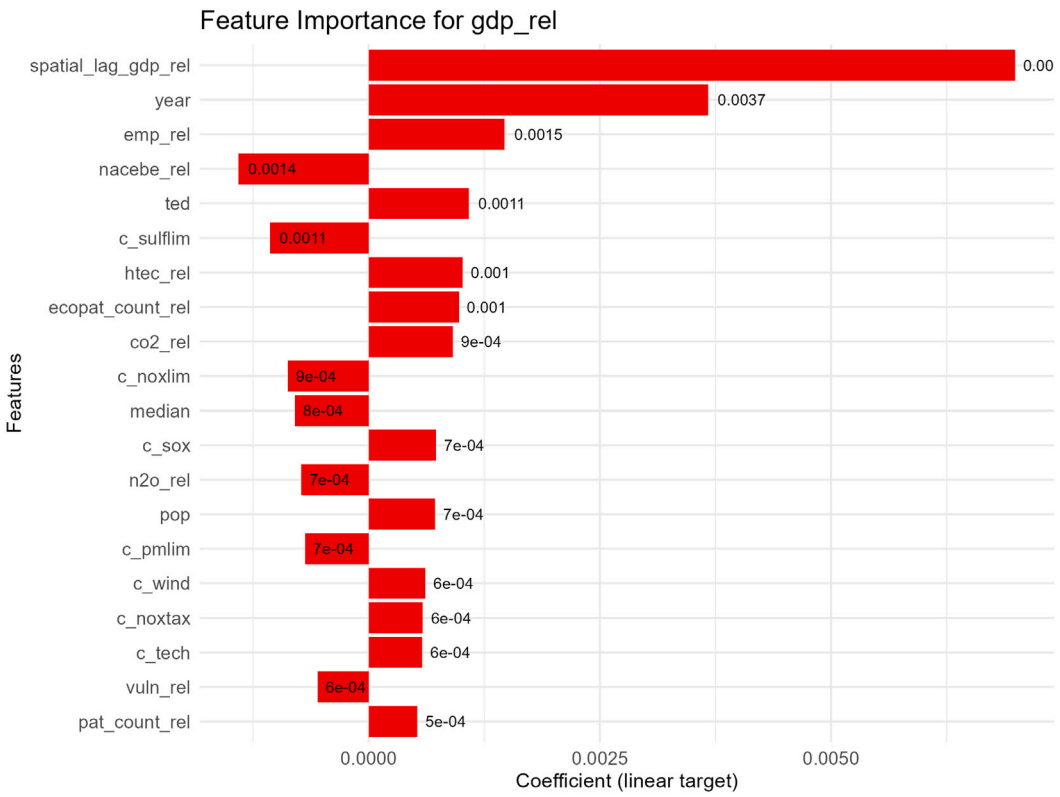

Fig. 4. Feature importance plot — Regional GDP
Notes: Feature importance plot indicating the relative contribution of predictors to the fitted model. The intercept ranked highest but was omitted for readability.

despite exhibiting statistically significant associations in the OLS regression. The same applies for CO_2. Conversely, in the ML analysis of GDP, employment in high-tech and knowledge intensive sector emerges as an important predictor in the feature importance analysis, notwithstanding its lack of significance in the OLS framework. This result can be attributed to the Elastic Net approach to managing multicollinearity: the high-tech variable effectively captures the variability associated with human capital endowments while maintaining a more direct correlation with GDP outcomes compared to other variables. The case of average disposable income yields particularly intriguing findings. Environmental regulations (EPS) appear to exert greater influence on regional income levels than GHG emissions, contrasting with the OLS results where EPS market measures failed to reach the 0.1 significance threshold, while the coefficient of CO_2 emissions is statistically significant (and of non-negligible magnitude). Gender employment gap analysis presents the most striking divergences between methodological approaches. While the OLS regression identifies unemployment rates as significant predictors, the Elastic Net feature importance analysis assigns minimal weight to this variable. Instead, EPS indicators and greenhouse gas emissions emerge as prominent determinants, supporting the hypothesis that women are not uniformly distributed across sectors with different levels of vulnerability to the sustainability transition, thereby linking environmental performance and protection mechanisms to gender equity outcomes in the labour market. These discrepancies highlight the value of a comparative approach, as different methods uncover complementary dimensions of the complex relationships between environmental performance, sectoral structures, and labour market outcomes. At the same time, they also highlight the limitations of traditional regression approaches (whose linear framework struggles to capture the multidimensional interactions underpinning labour market outcomes) and the advantages of machine learning methods, which, by accommodating complex and non-linear relationships, provide valuable insights into the intertwined dynamics involved in the just and sustainable transition.

4.3. Scenario results

This section discusses the regional outcomes of the four simulated scenarios, highlighting the differentiated effects on unemployment, GDP, disposable income, and gender employment gap across European regions. The results are provided in Figs. 7 to 9, which represent, respectively, the scenarios: (1) Enhanced innovative capacity; (2) Emission cap; (3) Labour market policies; (4) Policy mix scenario.

Starting from Scenario 1 *"Enhanced innovative capacity"* (Fig. 7), while innovation is often seen as a driver of economic growth and competitiveness, our findings suggest that focusing exclusively on boosting innovative capacity may lead to unintended negative

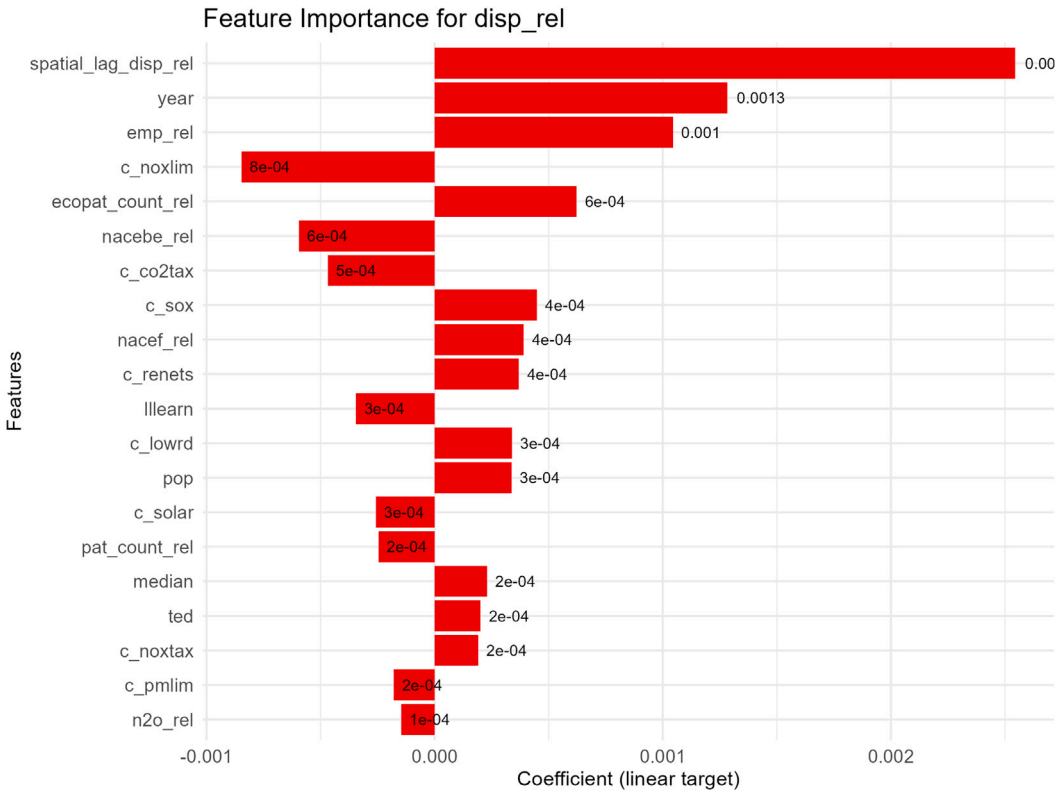

Fig. 5. Feature importance plot — Average disposable income
Notes: Feature importance plot indicating the relative contribution of predictors to the fitted model. The intercept ranked highest but was omitted for readability.

consequences. Unemployment changes vary across regions: many regions, especially in Northern Europe, including large areas of Sweden, Denmark, and Belgium display reductions in unemployment, whereas most of Eastern Europe, along with pockets of Southern and Western Europe — including areas in Greece and Spain — show increases. The employment gains in Northern Europe suggest that these regions capitalize on enhanced innovation to expand job opportunities. However, in Eastern Europe, structural labour market rigidities or sectoral mismatches might prevent innovation from translating into widespread employment benefits.

On the other hand, under this scenario, the effects on GDP are more scattered, with very heterogeneous outcomes coexisting within the same country. One notable exception is Poland, which is to benefit uniformly. Improvements are expected also in Mediterranean regions of Spain and France, and in Southern Italy. These positive changes in GDP align with the expectation that stronger innovation fosters economic growth, especially in regions lagging behind or characterized by less mature innovation ecosystems which have stronger learning scope (Barabuffi et al., 2025). In contrast, the negative effects in certain regions might signal trade-offs due to resource reallocation or competitive disadvantages due to disparities in absorptive capacity.

Compared to GDP outcomes, disposable income displays a few noticeable divergences: many Northern regions (e.g. Ireland, Benelux and Denmark) benefit, whereas most of France, and parts of Spain and Finland see limited or negative changes. Regions characterized by lower income levels (such as in Eastern Europe, Greece, regions in Central Italy and Southern Spain) seem to benefit relatively more. In several instances, we observe a divergence between GDP and disposable income outcomes, notably in regions such as Occitanie (France), Basilicata (Italy), and Southern Finland. This disparity suggests that innovation-driven economic growth does not always translate into widespread welfare improvements, as unequal access to opportunities can prevent many from benefiting. Since knowledge and capital accumulation may disproportionately favour certain groups (exacerbating inequality rather than reducing it), without inclusive policies, innovation risk deepening existing socio-economic disparities rather than fostering welfare for all.

The results on gender employment gap show a mix of positive and negative effects across Europe, with significant improvements in some regions (i.e., strong reduction in the gender employment gap), but also signs of widening disparities elsewhere. This variation suggests that fostering innovation (and, more broadly, innovation-led transitions) can support gender equality in employment when they generate opportunities in high-skill, knowledge-intensive sectors that tend to be more gender-inclusive. However, in regions where the labour market remains dominated by male-intensive or lower-skill sectors, or where structural barriers persist (e.g., limited access to STEM careers or care-related constraints), these benefits may not materialize. This evidence seems to align with recent Eurostat data, which show that while the EU gender employment gap has slightly narrowed in recent years, significant

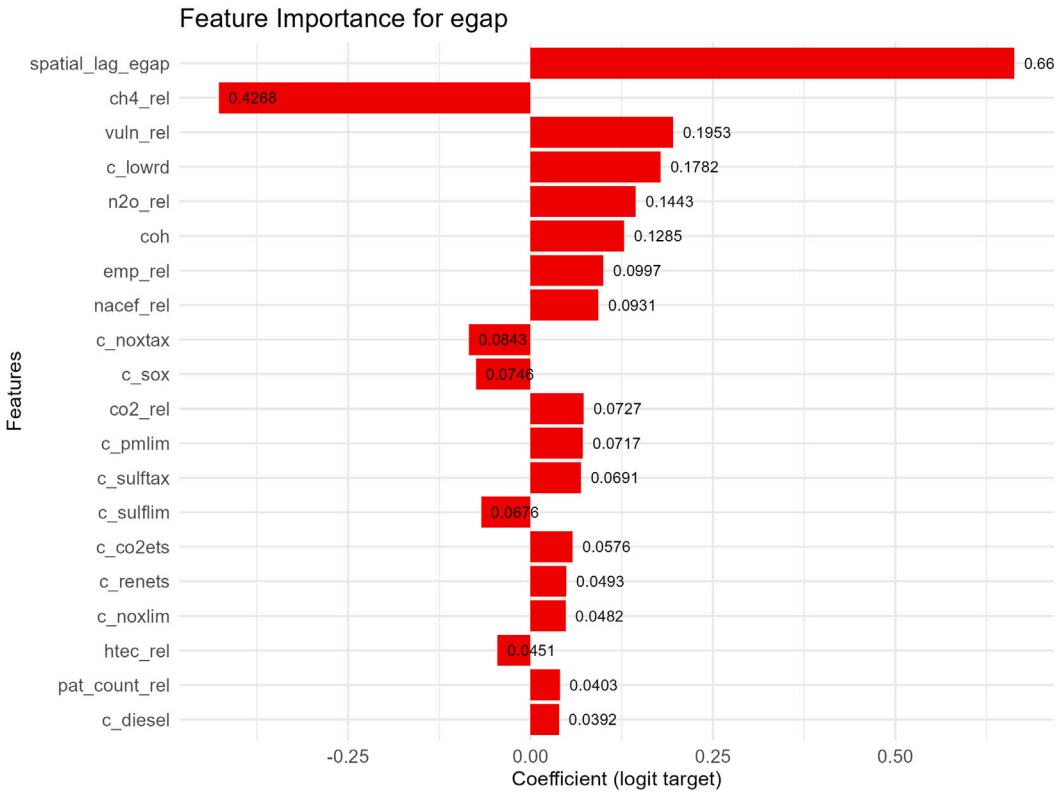

Fig. 6. Feature importance plot — Gender employment gap
Notes: Feature importance plot indicating the relative contribution of predictors to the fitted model. The intercept ranked highest but was omitted for readability. The dependent variable was logit-transformed to ensure EN predictions remain within the 0–100 range.

differences remain in female employment rates in technology-intensive sectors (i.e., men accounting for over two-thirds of the total, on average).[9] This underscores the need for complementary gender-sensitive policies to ensure that innovation-driven transitions do not reinforce existing inequalities.

Moving to Scenario 2 *"Emissions cap"* (Fig. 8), our findings highlight a more pronounced country effect, particularly evident in Hungary, Sweden, and Poland. This finding underscores the critical role of national measures, including early implementation of policy stringency and a proactive approach to green growth, in shaping regional outcomes under an emissions cap. While the labour market effects are predominantly negative — manifested in rising unemployment rates consistent with the literature discussed in Section 2 — it is noteworthy that many regions exhibit a reduction in unemployment. Indeed, our analysis indicates that 71 out of 199 regions are projected to experience employment growth.

The projection on GDP draws a mostly positive picture, with widespread growth patterns observed in Eastern and Northern Europe, as well as France, suggesting that the emission cap may be aligned with these regions' green transition goals (and current energy mix). In contrast, negative effects are more pronounced in Spain and other Central continental regions. However, the results in terms of disposable income show a more nuanced picture. While some European regions experience significant income gains (most notably in Ireland and Greece), most regions in France, Germany, Poland, Hungary, Sweden and Finland are characterized by very negative outcomes. The positive changes may reflect the policy's alignment with regional industrial transformation strategies, leading to income growth; negative effects may signal the higher costs of compliance with environmental policies. Occasionally, a divergence emerges between GDP growth and disposable income outcomes. For instance, while most regions in France are projected to experience GDP growth, they simultaneously face a decline in disposable income. Conversely, the opposite pattern emerges in Southern and Eastern Ireland, where an emission cap is associated with higher disposable income but a reduction in GDP. This divergence suggests that immediate improvements in households' capacity to consume, invest, and save may not align with broader economic growth. One possible explanation lies in a socio-political landscapes that prioritize corporations and capital accumulation in the first case, while favouring household benefits in the second. Additionally, in certain regions (such as in Southern Spain) an emission cap is projected to lead to increases in both GDP and disposable income, while simultaneously leading to higher

[9] https://ec.europa.eu/eurostat/web/products-eurostat-news/w/ddn-20231030-1

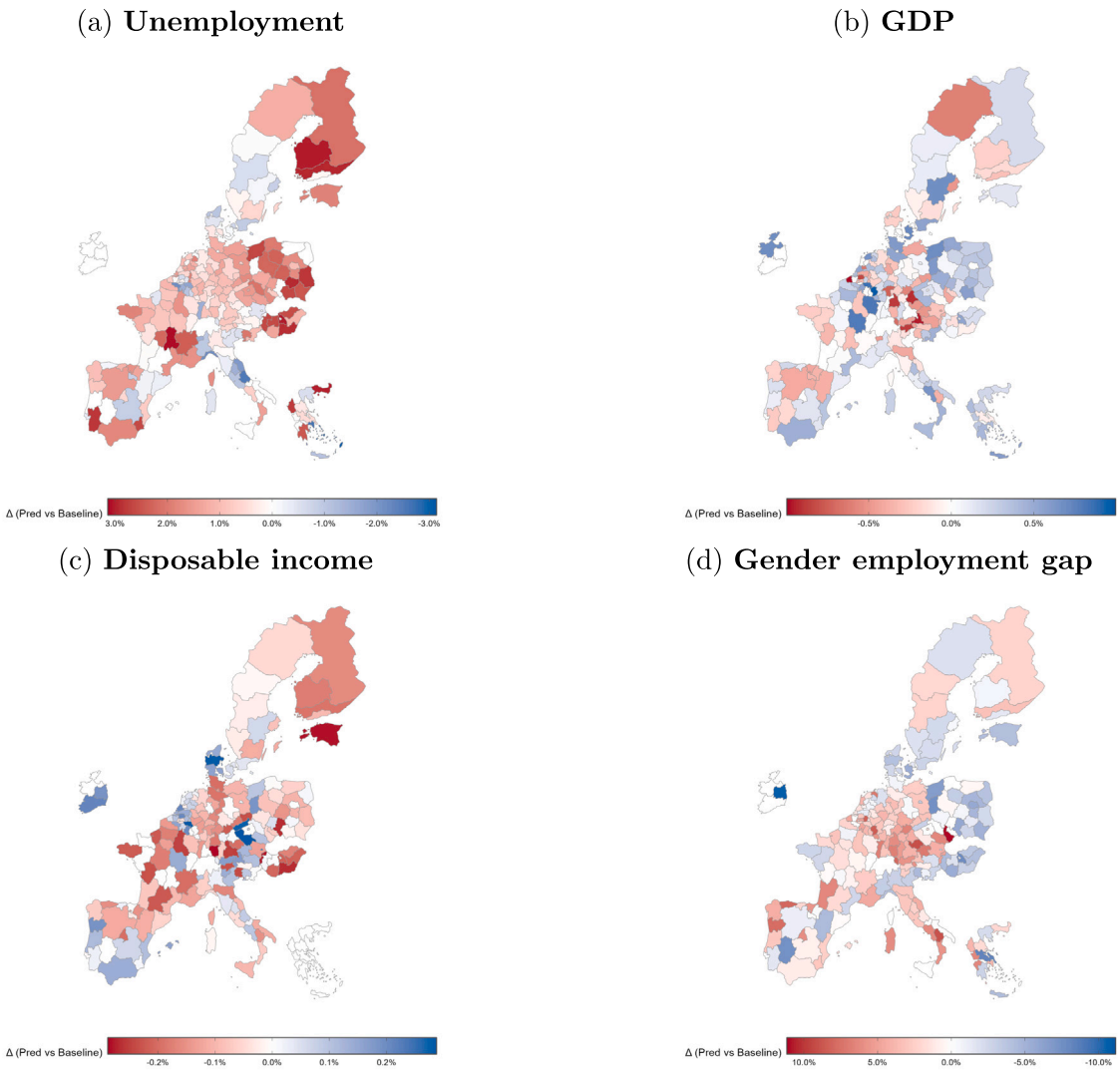

Fig. 7. Scenario 1 — Enhanced innovative capacity
Notes: White indicates no change; shades of blue show improvements over the status quo (*i.e.*, higher GDP and disposable income, lower unemployment or gender gap) and shades of red show worsening, using a per-map symmetric scale around zero; numbers are percentage-point changes from baseline.

unemployment rates. This finding provides an intriguing perspective on the complex interplay between economic performance and inequality, suggesting that positive macroeconomic indicators can sometimes mask underlying issues of social exclusion.

Similarly to the previous figure, also in this scenario the implication in terms of gender employment gap are quite heterogeneous across regions.

The results for Scenario 3, *Labour market policies* (Fig. 9), underline the complex relationship between labour market restructuring and socio-economic outcomes. In this scenario, unemployment declines in most regions, more markedly than in previous cases, though significant within-country disparities remain. These findings suggest that gradual yet sustained worker reallocation away from vulnerable sectors is critical to limiting labour market disruptions. These results strengthen the rationale for policy frameworks prioritizing reskilling and upskilling, in line with the aim and targets of the Just Transition Fund. Regarding GDP, our findings show that shifting away from vulnerable, low-value-added sectors toward services and high-tech industries generally experience widespread GDP gains. However, these gains are not consistently reflected in disposable income outcomes. In several areas (of Poland and Germany, namely in Śląskie and in the area of North Rhine-Westphalia), disposable income growth remains relatively weak despite significant GDP increases. In the Spanish regions of Navarre and Madrid, and in the Stockholm region, disposable income decreases, contrary to GDP growth. This divergence signals a potential risk that the green transition, while boosting overall economic output, may not translate into commensurate benefits for workers and households. This further underscores the critical need for policies that support up-skilling and re-skilling to prevent social distortions that extend beyond economic performance.

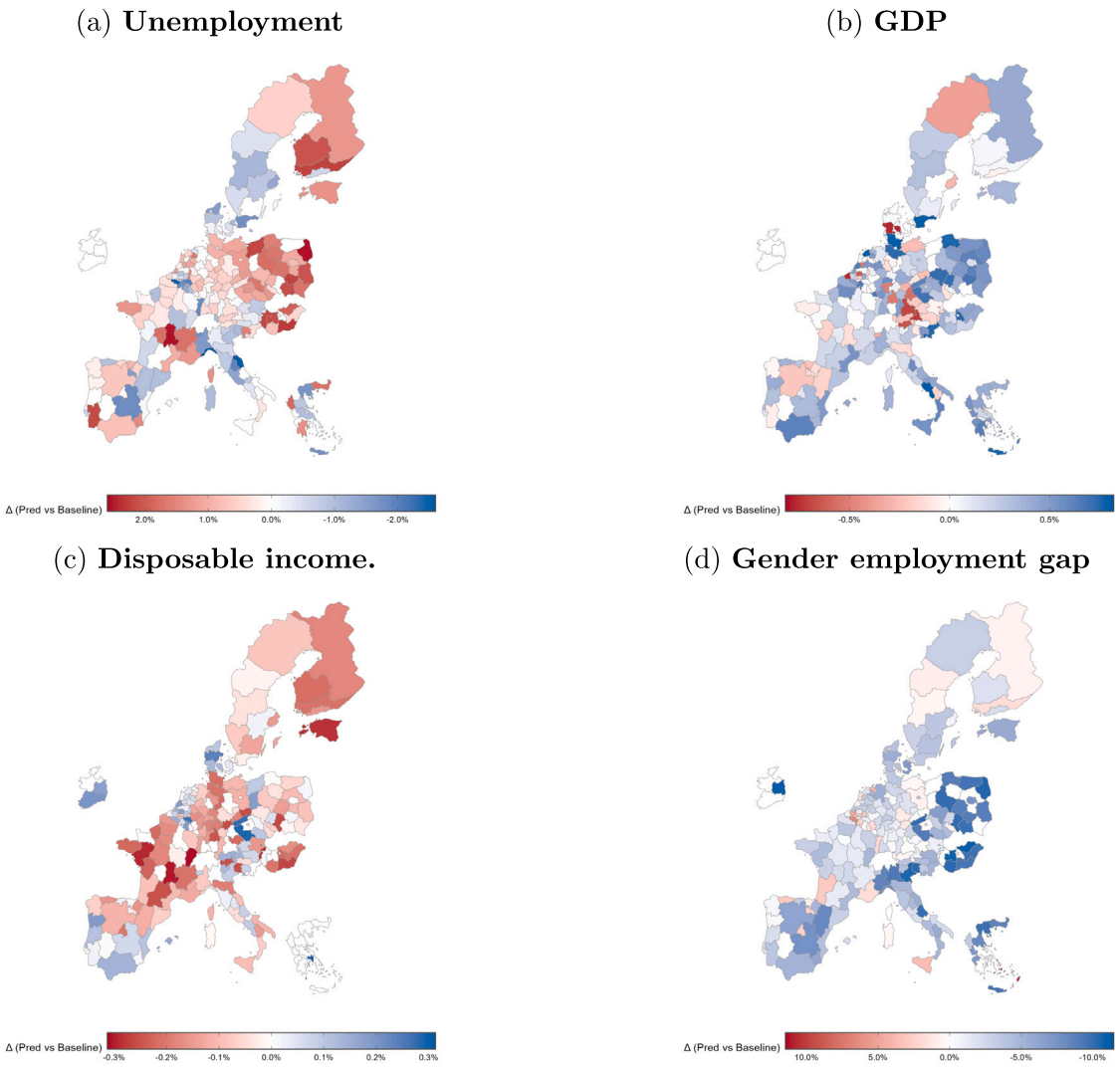

Fig. 8. Scenario 2 — Emissions cap
Notes: White indicates no change; shades of blue show improvements over the status quo (*i.e.*, higher GDP and disposable income, lower unemployment or gender gap) and shades of red show worsening, using a per-map symmetric scale around zero; numbers are percentage-point changes from baseline.

Furthermore, the gender employment gap follows a notably more negative trajectory, with the widest disparities observed so far, particularly across all regions of Germany and Eastern Europe. This finding raises equity concerns, and suggests that the labour market resilience to the green transition may disproportionately exclude vulnerable groups, exacerbating existing inequalities.

The results of Scenario 4, *Policy mix* (Fig. 10), closely resemble those of Scenario 3. From a methodological point of view, this similarity can be explained by the prominent role of sectoral composition variables in our predictions (see Section 4.2), but it also captures a well-established insight from the literature: labour market dynamics and the transition away from traditional employment represent the most disruptive aspect of the sustainability transition.

However, we observe that combining all three policy measures (i.e., enhanced innovation capacity, GHG emission reduction, and labour market transition) helps mitigate the negative effects on gender employment gaps, although it shows limited impact on other target indicators. This finding is particularly significant, as it suggests that comprehensive policy mixes can compensate for the disruptive effects of individual measures, thereby promoting greater inclusion and social justice during the green transition.

To provide a more concise assessment of the results across the different scenarios and to better capture distributive outcomes, we summarize our findings in Table 5. This further analysis reveals many relevant insights. First, we notice how scenario 4 produces, on average, the biggest improvement in all target variables (i.e., lower unemployment, higher GDP, higher income and lower gender gap), reinforcing the idea that a comprehensive policy action is the most beneficial when dealing with the multidimensional challenges of the sustainability transition. At the same time however, scenario 4 also yields the most detrimental distributional

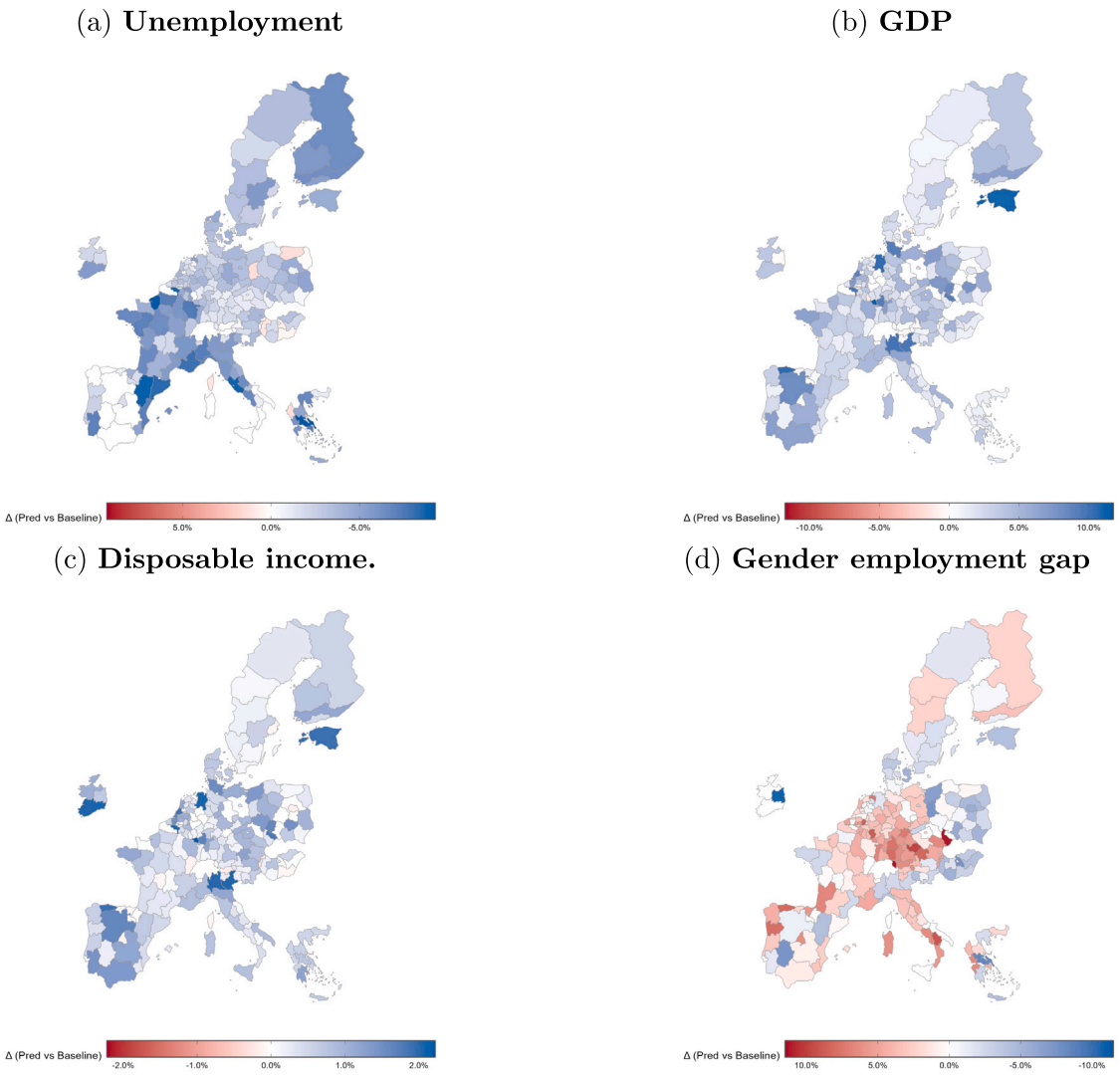

Fig. 9. Scenario 3 — Labour market policies
Notes: White indicates no change; shades of blue show improvements over the status quo (*i.e.*, higher GDP and disposable income, lower unemployment or gender gap) and shades of red show worsening, using a per-map symmetric scale around zero; numbers are percentage-point changes from baseline.

effects, as captured by the Gini index. In contrast, Scenarios 1 and 2 yield more equally distributed benefits (or costs), as shown by the lower Gini indices for unemployment, GDP, and disposable income, with an improvement compared to the observed values for 2019. It is worth highlighting that the gender employment gap, on the other hand, faces unfavourable distributional consequences in all scenarios. These findings hint at a possible equity-efficiency trade-off in sustainability transition policies, and act as a warning of possible conflicts between environmental goals and cohesion in the EU.

We also conduct a sensitivity analysis to test the robustness of our findings by re-estimating all three scenarios under four alternative shock intensities, i.e., ±5% and ±10% changes to the shocked variable (see Table 1 in Appendix). Across these specifications, the main patterns of regional heterogeneity and outcome remain consistent and the fluctuations in model results are substantially smaller than the changes applied to scenario parameters, providing strong evidence of the model's stability and the robustness of our comparative assessment across policy scenarios.

Lastly, to further analyse the distributional implications of our findings, we complement the scenario analysis by examining the characteristics of the regions experiencing the strongest positive and negative impacts (hereafter, "winners" and "losers"). For each scenario and target variables, we select the top and bottom 25% of regions based on predicted changes and compute the average values of key structural characteristics. The results, illustrated in Fig. 11, show that the regions benefiting the most tend to exhibit higher unemployment rates, larger gender employment gaps, and greater shares of employment in vulnerable sectors. At the same

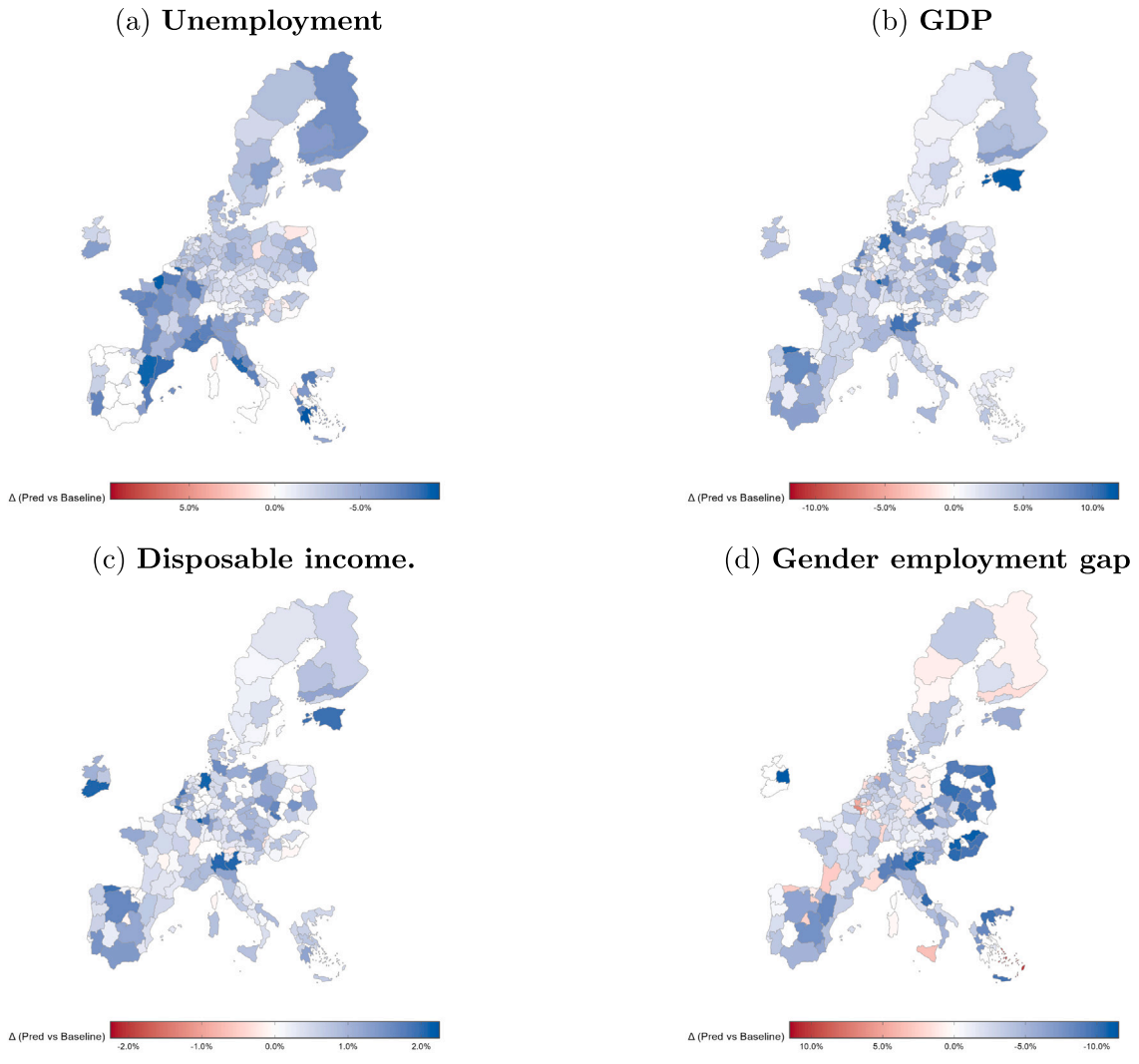

Fig. 10. Scenario 4 — Policy mix
Notes: White indicates no change; shades of blue show improvements over the status quo (*i.e.*, higher GDP and disposable income, lower unemployment or gender gap) and shades of red show worsening, using a per-map symmetric scale around zero; numbers are percentage-point changes from baseline.

Table 5
Mean and Gini index of actual vs. predicted outcomes under the four scenarios.

	Unemployment		GDP_rel		Disp_rel		Egap	
	Mean	Gini	Mean	Gini	Mean	Gini	Mean	Gini
Actual	6.59495	0.36870	0.03210	0.25218	0.01719	0.12174	11.14394	0.28164
Scenario 1 — Predicted	7.44429	0.32228	0.03131	0.19762	0.01692	0.11291	12.82930	0.31290
Scenario 2 — Predicted	6.90786	0.33080	0.03345	0.18494	0.01675	0.10928	7.68602	0.32009
Scenario 3 — Predicted	2.69753	0.59374	0.07219	0.31786	0.02493	0.19528	13.12435	0.30782
Scenario 4 — Predicted	2.56977	0.59151	0.07351	0.31069	0.02515	0.19512	7.50262	0.32553

Notes: A sensitivity analysis is provided in the Appendix.

time, they display lower levels of GDP per capita, lower employment in technological and knowledge-intensive sectors, weaker innovative capacity (as measured by eco-patents), lower CO2 emissions and — in most cases — lower level of disposable income. These findings suggest that under the policy shocks considered (whether isolated or in a policy-mix), structurally fragile regions and those facing specific transition risks are the ones that stand to gain the most in relative terms, whereas wealthier and technologically stronger regions tend to experience comparatively smaller improvements or even losses. This pattern suggests that, when a uniform

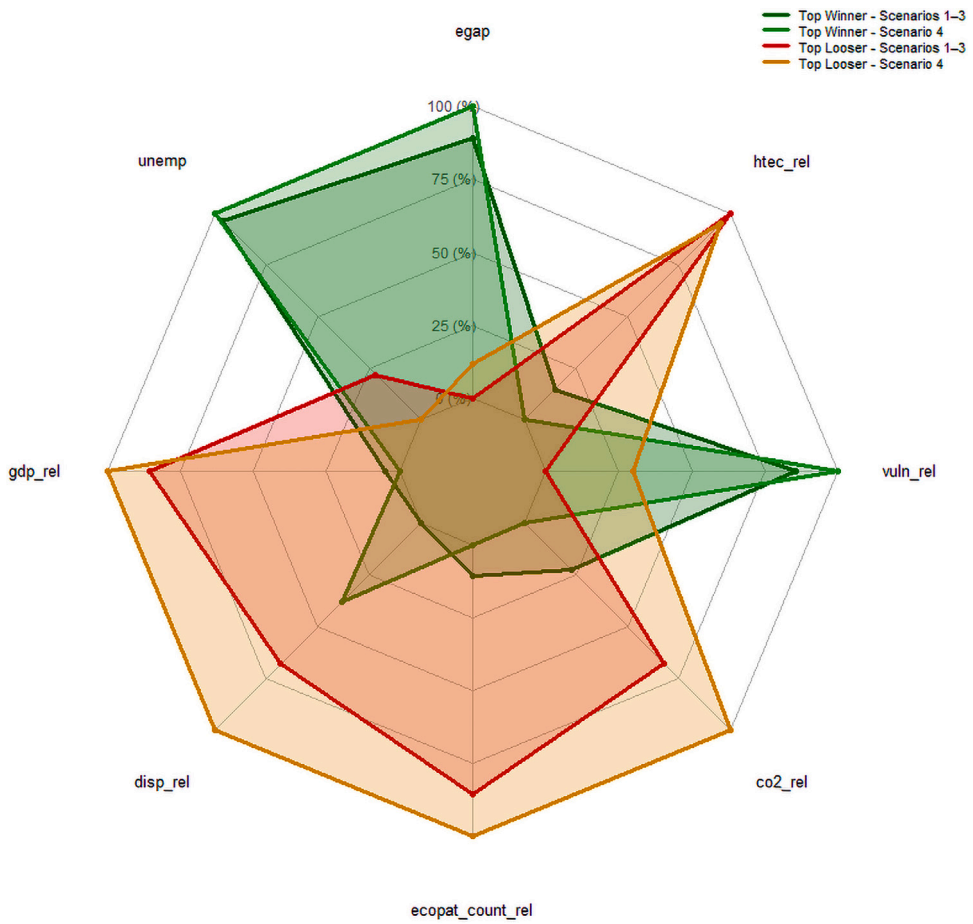

Fig. 11. Win–Lose Spider Plot.

shock is applied across all regions, lagging-behind regions benefit relatively more, while more affluent and technologically advanced ones show more limited gains.

5. Conclusions and further research

The analysis presented in this study highlights the complex and heterogeneous dynamics of sustainability transitions across subnational regions, demonstrating that policies, even if uniformly designed, can produce divergent socio-economic outcomes at the local level. While some areas benefit from GDP growth and higher income, others experience higher unemployment, increasing income disparities, and widening gender employment gaps. These findings reinforce the importance of including social justice and equity considerations into policy framework to ensure that sustainability transitions are not only environmentally effective but also socially inclusive.

Machine learning techniques, as employed in this study, offer a valuable tool for identifying local vulnerabilities and providing evidence-based recommendations to guide policy strategies. The results from the simulated scenarios (enhanced innovative capacity, emissions cap, labour market restructuring, the combined policy mix) suggest that sustainability transitions are neither linear nor uniformly beneficial across space. Innovation, a key driver of economic growth, does not inherently lead to inclusive development. Unequal access to opportunities and the concentration of benefits among certain groups may result in rising inequalities rather than fostering welfare improvements for all. Similarly, while policies aimed at emissions reduction can generate economic gains, they may simultaneously lead to rising unemployment, particularly in regions dependent on carbon-intensive industries. This suggests that positive macroeconomic indicators can sometimes mask underlying vulnerabilities, making it essential to consider local context when designing policy interventions. The results also highlight the potential risks that transition patterns pose to labour markets, and moving away from vulnerable sectors can have particularly adverse consequences in regions more exposed to the transition risks (where job displacement is likely to be more pronounced). Without targeted measures, the labour market adjustments necessary for a green transition risk exacerbating rather than alleviating social disparities.

These insights have significant policy implications, as our results suggest that a uniform, top-down approach to sustainability transitions may not be able to ensure equitable outcomes. Indeed, from one side, the impact of climate and energy policies (typically coordinated at the national level) is highly context-dependent, reinforcing the idea that one-size-fits-all solutions are insufficient. At the same time, this aligns with the intertwined evolution of the EU environmental and cohesion agenda, which jointly support the green transition but also the need for territorially differentiated policy strategies that consider both EU-level coordination and region-specific needs, capacities, and vulnerabilities.

In this context, the Just Transition Fund (JTF) emerges as a relevant instrument in the EU policy, designed to support place-based economic diversification and reconversion in regions most negatively affected by the net-zero transition through measures such as worker up- and reskilling, job-search assistance, and support for economic activities. However, while the JTF provides much-needed resources, it cannot fully address all the challenges associated with the sustainable transition. Its effectiveness ultimately depend on the ability of national and regional governments to implement broader transition strategies that go beyond short-term economic compensation and focus on long-term structural transformation. This includes strengthening labour market policies, expanding re-skilling and social-protection mechanisms, and adopting targeted innovation-diffusion and industrial-upgrading policies. Achieving a just and sustainable transition is not only a technological or economic challenge but fundamentally a social one, requiring policies that are both spatially sensitive and capable of reducing pre-existing inequalities rather than reinforcing them. Crucially, these interventions should prioritize regions identified as jointly fragile — both structurally and in terms of their exposure to transition risks — to maximize policy effectiveness and leverage region-specific capabilities to avoid widening territorial disparities.

While this study provides important contributions to understanding the socio-economic effects of sustainability transitions, it also opens several avenues for future research. Notably, our analysis has focused on the isolated effects of each policy intervention, and has treated the interactions among them only marginally. Future studies should explore the dynamic interplay across these dimensions, i.e., how emissions mitigation, innovation incentives, and labour market policies interact over time, leading to either reinforcing or counteracting effects. Future research should also explicitly incorporate additional policy drivers (such as welfare systems and education), as well as examine how the interaction between different levels of governance influences transition outcomes. Understanding how these policy domains intersect, overlap, or conflict will be key to designing coherent and just transition strategies across diverse territorial contexts. The success of such efforts, however, hinges on the availability of high-quality data capable of faithfully capturing local contexts.

CRediT authorship contribution statement

Valeria Costantini: Writing – original draft, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Elena Paglialunga:** Writing – original draft, Supervision, Methodology, Investigation, Data curation, Conceptualization. **Angela Zanoni:** Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Elena Paglialunga reports financial support and statistical analysis were provided by Italian Ministry of University and Research. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Recoding of regions to 2021 NUTS2

Croatia

In 2021, the region HR04 Continental Croatia (HR04) was split into Pannonian Croatia (HR02), City of Zagreb (HR05), and Northern Croatia (HR06). For this case, our approach involved creating a proportional relationship between the population of the new regions and HR04, based on population. In particular, after performing a linear extrapolation of the population of the smaller regions (available since 2013), the patent counts of HR02, HR05, and HR06 were proportionally assigned based on their share of the total population in HR04.

France

In the case of France, Regpat reports the code of the second-level metropolitan departments, under standard ISO 3166-2. In this case, it was sufficient to verify in which NUTS2 region the metropolitan department was located and to substitute the appropriate NUTS2 classification. Note that more than one metropolitan department can be contained in a NUTS2 region. Specifically:

1. FR21 was replaced by FRC1.
2. FR22 was replaced by FRH0.
3. FR23 and FR24 were both replaced by FRI1.
4. FR25 was replaced by FRC1.
5. FR26 was replaced by FRK2.
6. FR30 was replaced by FRJ1.
7. FR41 was replaced by FRB0.
8. FR42 and FR43 were replaced by FRK2.
9. FR51 and FR52 were replaced by FRF2.
10. FR53 was replaced by FRG0.
11. FR61 was replaced by FRD1.
12. FR62 was replaced by FRE1.
13. FR63 was replaced by FRK2.
14. FR71 was replaced by FRC1.
15. FR72 was replaced by FRG0.
16. FR81 and FR82 were replaced by FRJ2.
17. FR83 was replaced by FRL0.

Hungary

In Hungary, applications coming from the regions of Budapest (HU11) and Pest (HU12) are reported jointly under the code HU10. In this case, too, the patent counts for HU11 and HU12 were assigned according to population share.

Ireland

In Ireland, a similar approach was taken for regions IE05 and IE06, which replaced IE02 after the latest NUTS revision in 2016. The population of IE05 and IE06 was extrapolated when not available (before 2012); then the patent counts were proportionally scaled to reflect their share of the total population in IE02.

Table A.6
Distribution of actual vs. predicted outcomes and robustness checks.

	Unemployment			GDP_rel			Disp_rel			Egap		
Row	SD	Mean	Gini	SD	Mean	Gini	SD	Mean	Gini	SD	Mean	Gini
Actual (common)	4.75598	6.59495	0.36870	0.01495	0.03210	0.25218	0.00366	0.01719	0.12174	5.74846	11.14394	0.28164
scenario 1 — Predicted	4.73306	7.44429	0.32228	0.01082	0.03131	0.19762	0.00339	0.01692	0.11291	7.82303	12.82930	0.31290
scenario 1 — Robustness + 5%	4.73313	7.44390	0.32230	0.01082	0.03131	0.19763	0.00339	0.01691	0.11290	7.82297	12.83035	0.31288
scenario 1 — Robustness − 5%	4.73299	7.44469	0.32226	0.01082	0.03131	0.19761	0.00339	0.01692	0.11292	7.82308	12.82825	0.31292
scenario 1 — Robustness + 10%	4.73320	7.44351	0.32232	0.01082	0.03131	0.19764	0.00339	0.01691	0.11288	7.82292	12.83140	0.31286
scenario 1 — Robustness − 10%	4.73292	7.44508	0.32224	0.01082	0.03131	0.19761	0.00339	0.01692	0.11292	7.82314	12.82720	0.31294
scenario 2 — Predicted	4.52188	6.90786	0.33080	0.01079	0.03345	0.18494	0.00326	0.01675	0.10928	5.13508	7.68602	0.32009
scenario 2 — Robustness + 5%	4.52182	6.90776	0.33080	0.01079	0.03345	0.18494	0.00326	0.01675	0.10928	5.13460	7.68503	0.32009
scenario 2 — Robustness − 5%	4.52193	6.90796	0.33080	0.01079	0.03345	0.18495	0.00326	0.01675	0.10928	5.13557	7.68702	0.32008
scenario 2 — Robustness + 10%	4.52177	6.90766	0.33080	0.01079	0.03345	0.18494	0.00326	0.01675	0.10928	5.13412	7.68404	0.32010
scenario 2 — Robustness − 10%	4.52198	6.90806	0.33080	0.01079	0.03345	0.18495	0.00326	0.01675	0.10929	5.13605	7.68801	0.32008
scenario 3 — Predicted	3.42148	2.69753	0.59374	0.04989	0.07219	0.31786	0.01041	0.02493	0.19528	7.81840	13.12435	0.30782
scenario 3 — Robustness + 5%	3.37825	2.61044	0.60248	0.05229	0.07422	0.32303	0.01088	0.02534	0.20001	7.81840	13.12435	0.30782
scenario 3 — Robustness − 5%	3.46547	2.79002	0.58462	0.04750	0.07017	0.31245	0.00994	0.02452	0.19045	7.81840	13.12435	0.30782
scenario 3 — Robustness + 10%	3.33577	2.52829	0.61086	0.05469	0.07625	0.32797	0.01136	0.02576	0.20464	7.81840	13.12435	0.30782
scenario 3 — Robustness − 10%	3.51026	2.88846	0.57516	0.04511	0.06814	0.30681	0.00947	0.02411	0.18552	7.81840	13.12435	0.30782
scenario 4 — Predicted	3.23517	2.56977	0.59151	0.04983	0.07351	0.31069	0.01044	0.02515	0.19512	5.14099	7.50262	0.32553
scenario 4 — Robustness + 5%	3.19426	2.48645	0.60026	0.05223	0.07554	0.31602	0.01091	0.02556	0.19977	5.14047	7.50230	0.32551
scenario 4 — Robustness − 5%	3.27681	2.65828	0.58239	0.04743	0.07148	0.30511	0.00997	0.02474	0.19037	5.14152	7.50294	0.32554
scenario 4 — Robustness + 10%	3.15406	2.40786	0.60869	0.05464	0.07757	0.32111	0.01139	0.02597	0.20433	5.13994	7.50198	0.32549
scenario 4 — Robustness − 10%	3.31921	2.75248	0.57290	0.04503	0.06945	0.29926	0.00950	0.02433	0.18553	5.14204	7.50326	0.32556

Notes: SD = standard deviation across NUTS2 regions; Gini computed on regional levels.

Lithuania

For Lithuania, Regpat does not distinguish between regions LT01 (Sostines regionas) and LT02 (Vidurio ir vakary Lietuvos regionas). Instead, it codifies all applications as coming from LT00. The patent counts for LT01 and LT02 were adjusted based on their share of the total Lithuanian population.

Poland

Several regions in Poland were recoded following the 2018 revision.

1. PL11 was replaced by PL71.
2. PL31 was replaced by PL81.
3. PL32 was replaced by PL82.
4. PL33 was replaced by PL72.
5. PL34 was replaced by PL84.

Another couple of regions in Poland, PL91 and PL92, resulted from the disaggregation of the previous PL12 region. In this case, the patent counts were scaled according to their population share (extrapolation was necessary before 2014).

Descriptive statistics of target variables under scenarios and sensitivity analysis

Table A.6 reports the results of a sensitivity analysis in which the original scenario parameters are subjected to variations of ±5% and ±10%. Note that the sensitivity tests confirm the robustness of our results, as all three metrics exhibit variations only in the decimal places for all target variables and under all four scenarios.

Data availability

Data will be made available on request.

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