4th INTERNATIONAL CONFERENCE ON ECONOMIC STATISTICS

STATISTICAL MODELS FOR THE ECONOMIC TRANSITION: THE NEW CHALLENGE IN A DEVELOPING WORLD

Book of short papers

Editors:
Vittorio Nicolardi
Caterina Marini

UNIVERSITÀ DEGLI STUDI DI BARI ALDO MORO
DIEF DIPARTIMENTO DI ECONOMIA E FINANZA
SMEA
SIS Società Italiana di Statistica

ICES 2026 - 4th International Conference on Economic Statistics

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ISBN 978-88-88793-74-0

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Acknowledgements:
We are grateful to the University of Bari Aldo Moro and the following sponsors for their economic and logistic support for ICES 2026 Conference:
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Preface

The global transformations that are reshaping the structural economic connections in the world markets are the core of the economic and social transition we have been living through over the last two decades. The inevitable changes, which are the result of the process in progress, have their consequences for all aspects of the human life, not only those strongly related to the economic developments, such as production and consumption, but also those connected to the socio-demographic equilibria. All scientific fields are being called upon to develop new statistical-economic methodologies and new interpretative approaches to better understand current and future scenarios underlying these phenomena. In this perspective, the effects of climate change and the implications of the ongoing transitions represent an essential part of the picture.

The volume collects a selection of short papers that were presented at *the 4th International Conference on Economic Statistics (ICES)*, held at the University of Bari Aldo Moro (Italy) on 5 - 6 February 2026.

Papers provide a wide overview of the most innovative analytical approaches, both methodological and applied, to better understand current and future scenarios underlying the socio-economic phenomena and their transition in a changing world, with a particular focus on the themes of sustainability and innovation.

The conference has explored the challenging opportunities of the ongoing transitions and the papers included in this volume reflect the multiplicity and diversity of the conference program that covered many topics such as labour market, time-dependent economic-financial data, sustainable growth and dynamics, regional competitiveness, digitalisation and technology in the framework of statistical models, input-output economic models, new indicators and data collection, time series and spatial analysis, environmental accounting, machine learning and artificial intelligence.

ICES is an annual event created to foster the scientific debate within the Italian community of the economic statisticians. This 4th ICES edition held in Bari opened up the scientific debate not only at the academic international level but also among institutional entities. In fact, it saw the participation of scholars from universities abroad and representatives of leading Italian research institutions.

Bari (Italy)
February 2026

Vittorio Nicolardi
Caterina Marini

Contents

A Capability-Based Assessment of Urban Well-Being in Rome

Marusca De Castris and Chiara Sciascia

Abstract This paper develops a capability-oriented framework to assess urban well-being in the city of Rome. Moving beyond income-based metrics, the study operationalizes the Capability Approach through a multidimensional index that distinguishes between functionings, capabilities, and conversion factors across eight domains of urban life: education, economic opportunities, environment, housing, mobility, culture and leisure, safety, and health. The paper contributes to the literature on urban inequality by providing a methodologically transparent and replicable framework for evaluating well-being in metropolitan contexts.

Key words: capability approach, urban well-being, composite index

1 Introduction

Urban inequalities increasingly challenge European metropolitan areas, where economic growth and infrastructural investment coexist with persistent spatial disparities. In Rome, decades of urban development policies have failed to overcome a marked core–periphery divide, particularly affecting districts located beyond the Grande Raccordo Anulare (Lelo et al., 2019). Conventional indicators such as income or employment rates provide only a partial account of these inequalities, as they overlook the multidimensional and spatially embedded nature of urban well-being.

To address this limitation, this paper adopts the Capability Approach (CA), which conceptualizes well-being in terms of individuals' real freedoms to achieve valued ways of being and doing (Sen, 1993; Nussbaum, 2011). These freedoms depend not only on resources, but also on the social, institutional, and environmental conditions—conversion factors—that shape how resources are transformed into outcomes

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(Robeyns, 2005). Applying this framework to Rome, the paper asks whether a capability-based assessment can reveal forms of territorial inequality that income-based metrics fail to capture.

2 Theoretical Background

The CA has been widely used to assess development, poverty, and well-being, offering a normative alternative to resource-based and utilitarian approaches (Sen, 1999; Chiappero-Martinetti & Roche, 2009). In urban contexts, the approach is particularly relevant, as cities concentrate both opportunities and constraints, mediated by spatial arrangements and governance structures (Biggeri & Ferrannini, 2014).

Recent literature emphasizes that urban well-being is shaped by institutional quality, accessibility of services, environmental conditions, and opportunities for participation, rather than income alone (Ferrara & Nisticò, 2015; Ehrlich & Overman, 2020). Scholars have also highlighted the importance of non-compensatory measurement strategies, arguing that allowing trade-offs across dimensions risks masking severe deprivations in essential domains (Mazziotta & Pareto, 2016; Alaimo, 2022). Building on this strand, the present study integrates the CA with a multidimensional, non-compensatory index tailored to the urban scale.

3 Analytical Framework and Data

The empirical framework distinguishes three analytical components within each domain of urban life: functionings (achieved states), capabilities (real opportunities), and conversion factors (structural conditions enabling or constraining those opportunities). Eight domains are considered: education, economic opportunities, environment, housing, mobility, culture and leisure, safety, and health.

A total of 35 indicators are selected based on conceptual relevance, data availability, and robustness. Data are drawn from the Italian National Statistical Institute (ISTAT), municipal open data platforms, and official reports, and are aggregated from sub-municipal units to Rome's fifteen districts. This aggregation allows comparison across districts while preserving underlying spatial heterogeneity.

4 Methodology

The Urban Well-Being Index is constructed using a non-compensatory methodology based on the Mazziotta–Pareto Index (MPI) (Mazziotta & Pareto, 2016). Indicators are first standardized and adjusted for polarity, ensuring that higher values

consistently correspond to better outcomes. The MPI combines the mean performance across indicators with a penalty for imbalance, thereby reducing scores for districts that perform unevenly across dimensions.

This approach reflects a core principle of the CA: severe deprivation in one domain (e.g., health or mobility) cannot be ethically compensated by advantages in another (e.g., income or culture). The index is computed both as an overall measure and by domain, enabling identification of the specific drivers of territorial inequality.

5 Results

The results reveal substantial spatial disparities in multidimensional well-being across Rome. Central districts (notably Districts I and II) consistently rank highest, benefiting from dense institutional, cultural, and infrastructural endowments. Peripheral districts, particularly Districts VI and XV, display systematic disadvantages across multiple domains, including mobility, economic opportunities, safety, and health.

Importantly, the comparison between average income and the multidimensional index shows only partial overlap. Some districts with moderate income levels perform poorly in overall well-being due to weak conversion factors, while others with relatively low-income exhibit strengths in specific domains, such as environmental quality. These findings confirm that income alone is an insufficient proxy for urban well-being and that spatial and institutional conditions play a decisive role in shaping capabilities.

6 Discussion and Policy Implications

The evidence highlights a complex geography of urban inequality in Rome, characterized by cumulative disadvantages in peripheral areas. From a policy perspective, the findings suggest that redistributive measures based solely on income are unlikely to address these disparities effectively. Instead, interventions should target key conversion factors, including access to public transport, healthcare, cultural infrastructure, and safe public spaces.

More broadly, the study supports a place-based approach to urban policy, aligned with recent calls for integrating justice-oriented frameworks into metropolitan governance (Crisp et al., 2024; Stern & Kissinger, 2025). By explicitly distinguishing between functionings, capabilities, and conversion factors, the proposed framework offers policymakers a diagnostic tool to identify where and how interventions can expand substantive freedoms.

Acknowledgements: This work has been supported by MIUR, grant number 2022XRHT8R - The SMILE project: Statistical Modelling and Inference for Living the Environment.

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A Deep Reading of the Tourism Sector in the TSA Framework

Sandra Maresca and Ilaria Piscitelli

Abstract In a TSA framework the role directly played by tourism sector is highlighted consistently with the rest of national economy.
The TSA expressly measures the direct effects of tourism consumption within the economy, providing information on how much internal wealth is generated by the demand for goods and services from visitors. This is the main result obtained by the TSA and constitutes the fundamental basis for measuring indirect effects implementing an integrated methodology based on TSA indicators and on IO tables.
The mobility of people also has environmental repercussions on the country visited. In Italy the TSA has long been integrated with the environmental satellite account on atmospheric emissions.

Key words: Tourism Satellite Account (TSA); national accounts; tourism expenditure, tourism, environment.

1 Introduction

While the system of official tourism statistics already provides a large amount of basic information, the main value added of a TSA consists of integrating those data in a single, methodological and conceptual framework, derived from (and strictly connected to) the core of national accounts. Accordingly, a TSA allows the tourism sector to be highlighted within the national accounts as an industry taken as a whole and to describe and measure its role in the reference economy. From this point of view, the TSA plays the role of a rigorous instrument for assessing the importance of tourism flows and expenditures on production activities, consumption and employment.

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The information organized in the TSA expressly measures the direct effects of tourism consumption within the economy, providing information on how much internal wealth is generated by the demand for goods and services from visitors. The direct effect of tourism is the main output obtained by the TSA, which therefore is not able to represent the whole potential of the tourism sector but nevertheless constitutes the fundamental basis for measuring indirect effects. For this purpose, the IO tables are fundamental because they describe sectoral interdependencies and allow for a broad analysis of the effects of tourism demand on all production sectors.

In Italy the TSA has long been integrated with the environmental satellite account on atmospheric emissions. The result is an integrated economic and environmental account of tourism that combines the economic measurements of the TSA with those on emissions flows. The integrated account is compiled by tourism industries, for each of those, the contribution to emissions of some of the main atmospheric pollutants is provided.

2 Approach and methodology

Compiled according to the international guidelines [5,6], the TSA for Italy privileges the use of official sources based on (and following) international methodological standards. These sources are divided into two main types: sectoral surveys on tourism (carried out by Istat and the Bank of Italy) as well as national accounts data.

The methodology implemented for the Italian TSA is characterized by a strong level of integration of the sources used, whose basic information allows to develop a mixed approach: top-down for the estimation of tourism expenditure, bottom-up for the production account of tourism and other industries [4].

The tables that are part of the official release of the Italian TSA follow international standards for internationally comparable characteristic products and industries (accommodation, catering, transport, travel agency services, etc.), while specific tourism characteristic goods of Italy (for example some gastronomic products, leather goods, etc.) have been carefully selected and feed an eleventh category of product and industry defined respectively ‘Shopping and Retail of characteristic goods’, specific to the national context [3].

The almost exclusive use of official sources for the compilation of the Italian TSA ensures the quality of the final data and a strong reliability and replicability of final estimates.

In Italy the compilation of the TSA at national level is now a consolidated experience. However, in some cases, such as the tourism expenditure of the specific products, new data sources have been explored and used in the estimation process. In this respect, for the compilation of TSA2023 [1], Istat has integrated the usual sources of data with new administrative data on tax refunds obtained from the Italian Customs Agency, in order to improve estimation of international tourism expenditure for the item "Shopping".

The final reconciliation of the tourism sector on both the supply and the demand sides, that is the TSA Table 6, is an excellent test to evaluate the consistency of national accounts data from which the TSA is derived. This is a typical aspect of satellite accounting, as it is an expansion, and a focused representation of specific phenomena included in the overall framework of central accounting

Furthermore, in Italy the TSA has long been integrated with the environmental satellite account on atmospheric emissions. The result is an integrated economic and environmental account for tourism that combines the economic measurements of the TSA with those on emissions flows.

3 The structural characteristics of Italian tourism.

In Italy, according to the TSA, the tourism sector directly contributes on average approximately 5-6% of total value added and over 5% of GDP.

For the TSA2023 indirect effects were estimated for the first time in addition to direct ones [1].

Table 1: Direct, indirect and total requirements coefficients of domestic production inputs

Sector	***direct***	***total***	***indirect***
Agriculture, forestry and fishing	0.31	1.57	1.26
Industry	0.46	1.88	1.42
Construction	0.60	2.17	1.57
Wholesale	0.51	1.92	1.41
Tourism sector	**0.44**	**1.82**	**1.38**
Other services	0.41	1.73	1.33

Source: National Accounts, Istat – elaborations of I-O tables and TSA2023

The analysis of sectoral interdependencies allows to measure the impact on the entire economy generated by tourism consumption. Tourism is both an integral part of GDP as a constituent sector of the Italian economy and an economic driver that determines the level of not only its own output, but also that of other sectors of the economy. This impact occurs through tourism's contribution to aggregate demand, that is, the demand for goods and services in the economy as a whole.

These broader effects were estimated through processing of the input-output tables and the tourism consumption estimated within the TSA 2023 – table1. With reference to the tourism sector, they go beyond the tourism sector's mere accounting contribution, taking into account the interconnections between productive sectors. In short, tourism consumption spreads across the economy at multiple levels: it begins with a direct impact on tourism sector, extends to indirect impacts on suppliers and other sectors.

In 2023, the direct impact of tourism consumption generates 106.8 billion GDP, which becomes 206.4 billion if indirect effects are also considered [1].

The above table 1 shows as the two macro sectors of Industry and Construction are those mostly impacted (directly and indirectly) by the behaviour of the demand. Compared to them, but also to other sectors, tourism has a lesser capacity to spread the propulsive effect of tourism consumption to the entire economy: in the macroeconomic distribution shown in the table 1, the tourism sector is ranked ahead only of “Agriculture” and “Other services”.

As a phenomenon strictly linked to people mobility, tourism not only has economic repercussions, but also an environmental footprint, with production activities contributing to polluting air emissions, for example, and visitors contributing to resource consumption.

According to the integrated economic and environmental accounts for tourism [2], in 2023 in Italy tourism sector is responsible for the 5,1% of total emission of CO2 and others main air pollutants, for the 11,6% of the acidifying pollutants, for the 3,6% of energy use. Specifically, the water passenger transport industry is the one that has the worst environmental impacts.

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A Holistic Green Indicator for Tourism Sustainability Across Italian Provinces

Riccardo Gianluigi Serio, Maria Michela Dickson, Diego Giuliani and Giuseppe Espa

Abstract This study develops a spatial composite indicator of environmental effort in Italian tourism. Using the adoption of twelve eco-labels and environmental management schemes as proxies for sustainability investment, we apply Geographically Weighted Principal Component Analysis (GWPCA) to construct a holistic index that captures spatial heterogeneity. The indicator is then analysed through a Spatial Durbin Error Model (SDEM) to identify economic, environmental and spatial drivers of adoption. Results show that tourism intensity, income and environmental quality positively influence certification uptake, while air pollution and cultural congestion have negative effects.

Key words: Sustainable tourism, Environmental indicators, GWPCA, SDEM, Spatial spillovers

1 Introduction

Sustainable tourism measurement has expanded for decades, yet the literature repeatedly flags a practical problem: many sustainable tourism indicator systems capture states/pressures more than actual effort, and implementation is constrained by data gaps, governance frictions, and the tendency to measure "what is available"

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rather than "what matters" (UNWTO, 2004; Miller & Torres-Delgado, 2023; Torres-Delgado & Saarinen, 2014). The present paper aims to respond by shifting the measurement target from "how sustainable a destination looks" to "what destinations actually do" to be sustainable, proxied by eco-label and certification adoption. Our aim is to respond to three research hypotheses: **H1:** Is higher tourism intensity associated with higher certification uptake? **H2:** Is better baseline environmental performance positively associated with eco-certification uptake? **H3:** Is there positive spatial dependence and diffusion effects among neighbouring provinces?

Following OECD/JRC principles (OECD/JRC, 2008), the present paper proposes a spatially explicit composite indicator of environmental effort in tourism, constructed using Geographically weighted principal component analysis (GWPCA), at the provincial level in Italy (Cartone & Postiglione, 2021). Then, to assess the drivers of this holistic green indicator, we adopt the Spatial Durbin Error Model (SDEM) to model local spillovers in the covariates while simultaneously controlling for spatial autocorrelation in the error term, which may arise from unobserved common factors.

2 Construction of the holistic green indicator

The empirical analysis uses a cross-section of 107 Italian provinces (NUTS-3) in 2022, combining tourism and socio-economic covariates with twelve certification variables capturing public/governance and private/firms sustainability initiatives. Certification inputs begin as non-negative counts (e.g., Blue Flag marinas/municipalities/beaches; EU Ecolabel hotels; Green Key; BIO Hotels; EarthCheck), then they are transformed into per-capita intensities (per 100,000 residents) and standardized as z-scores, ensuring directional consistency ("higher = more adoption"). In the building of the indicator, standard PCA imposes a single covariance structure and global loadings, which can be misleading, as in the present case, when spatial heterogeneity is present (Cartone and Postiglione, 2021). So that, the use of GWPCA relaxes this bond, by estimating local covariance matrices using kernel weights, producing location-specific loadings, and enabling the mapping of locally dominant dimensions (Fotheringham et al., 2002; Harris et al., 2011). Provinces with higher values are interpreted as exhibiting more intense and diversified adoption of tourism-related certifications, conditional on local correlation structures.

3 The Spatial Durbin Error Model (SDEM)

The holistic index is related to macro-endowments and contextual factors. By implementing SDEM, we account for spatially structured unobservable (error dependence) and covariate spillovers through spatial lags. The model is defined as:

$$y = X\beta + WX\theta + u, \qquad u = \lambda Wu + \varepsilon, \qquad \varepsilon \sim N(0, \sigma 2In)$$

where y is the $n\times1$ vector of the dependent variable (the holistic green indicator), and X is the $n\times k$ matrix of explanatory variables. W represents the $n\times n$ non-negative spatial weight matrix describing the connectivity between provinces; specifically, non-zero elements w_{ij} indicate that province j is a neighbour of i. The matrix W is row-standardized, ensuring that the elements of each row sum to unity.
Results are presented in Table 1. We apply the SDEM to disentangle direct and indirect (spillover) effects on our response variable. Covariates are the number of overnight stays, t value added in tourism-related services ("Tourism VA") and PM10 ("Pollution"). Ordinary Least Squares (OLS) model is used as benchmark.

Table 1: Results of SDEM (OLS benchmark). Standard errors in parentheses. * Variables are per capita.

Variable	***SDEM (direct)***	***SDEM (indirect)***	***OLS***
(Intercept)	−0.005	−0.005	−0.755∗∗
	(0.786)	(0.786)	(0.346)
*Overnight stays	0.065∗∗∗	0.050∗	0.066∗∗∗
	(0.015)	(0.030)	(0.016)
*Tourism VA	0.169∗∗	0.371∗∗	0.130
	(0.082)	(0.174)	(0.088)
*Pollution	−0.139∗∗∗	−0.010	−0.151∗∗∗
	(0.039)	(0.079)	(0.043)
Spatial error parameter λ	0.451∗∗∗	-	-
	(0.101)		

4 Results and Discussion

Results from the SDEM confirm that tourism intensity is a key driver of certification uptake. Overnight stays show a positive and highly significant direct effect and a positive indirect effect, indicating that more tourism-intensive provinces adopt more certifications, and that part of this association diffuses through neighbouring territories. This confirms H1. Environmental context is consistent with the expected pattern once pollution is interpreted as "worse environment". Pollution is negative and highly significant in the direct effect, implying that provinces with better baseline environmental conditions (lower pollution) exhibit higher certification uptake, confirming H2. The indirect effect of pollution is not significant, suggesting that environmental quality is mainly a local condition in this setting rather than a spatially transmitted factor. Finally, the spatial specification provides strong evidence of interdependence. The spatial error parameter is positive and significant, pointing to spatially correlated unobservable, and tourism value added displays a significant positive spillover, reinforcing H3, namely the interpretation that

sustainability adoption follows regional diffusion and clustering mechanisms linked to tourism specialization

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A Multi-Method Text Mining Analysis of AIFA Drug Innovation Assessment Reports

Carlotta Galeone

Abstract Since 2017, AIFA assesses drug innovativeness based on therapeutic need, clinical value, and evidence quality. This study applies text mining to the 2017–2025 report corpus to explore how innovation is conceptualized. Methodology includes pre-processing, dictionary creation, and sub-corpus analysis (Approved Innovation vs. Not Approved Innovation) via word clouds and semantic networks and topic modeling. Furthermore, Correspondence Analysis (CA) maps latent associations between keywords and regulatory outcomes. This longitudinal analysis provides a data-driven framework to enhance transparency and understanding of institutional decision-making in the Italian pharmaceutical landscape.

Key words: Drug Innovativeness, Text Mining, Correspondence Analysis

1 Introduction

Since 2017, the Italian Medicines Agency (AIFA) has published detailed innovation assessment reports for newly authorized drugs whose manufacturers have formally requested such recognition [1]. These evaluations are based on a multidimensional framework: therapeutic need, added clinical value, and quality of evidence. Beyond their immediate regulatory function — which determines fast-track access, pricing negotiations, and eligibility for dedicated national innovation funds — these reports constitute a significant and largely untapped source of information. They offer a unique view into how pharmaceutical innovation is conceptualized, articulated, and communicated within a highly specialized institutional setting.

Despite their strategic value, these documents had not been analyzed using automated text mining approaches until now. This study fills that gap by examining the complete corpus of AIFA reports released between 2017 and 2025. By shifting the focus from individual clinical evaluations to a large-scale textual analysis, the project

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aims to identify recurring linguistic patterns, latent thematic clusters, and the evolving logic of the regulatory body. Ultimately, the research seeks to uncover how institutional language shapes the distinction between "Approved" and "Not Approved" innovation status, providing a deeper understanding of the criteria used to define pharmaceutical excellence in Italy.

2 Methodology

The methodological framework was developed by a working group comprising Daniele Pirotta, Andrea Marletta (Bicocca Applied Statistics Center - BASC), and Carlotta Galeone, with the support of ISPOR Chapter Rome. It utilizes a multi-stage text mining pipeline starting with the compilation of a 294-report corpus, followed by a rigorous pre-processing phase — including text cleaning, tokenization, stop-word removal, and term normalization — to ensure textual standardization [5].

The analysis employs two primary analytical approaches. First, a dictionary of the most frequent terms was generated and visualized through word clouds [3] and semantic networks (N-grams) to detect dominant topics and conceptual links [6]. Second, to verify the association between linguistic markers and regulatory outcomes, the corpus was divided into two sub-corpora based on the assessment result: "Approved" and "Not Approved" innovativeness status. Statistical models were then applied to these subsets to determine if the presence or absence of specific keywords significantly correlates with a successful innovativeness claim.

Furthermore, a longitudinal perspective was adopted to explore the temporal evolution of influential terms and topics throughout the 2017–2025 period, mapping how the institutional discourse on drug value has adapted to emerging clinical and economic challenges.

Finally, Correspondence Analysis (CA) [4] was integrated into the workflow. Applied to the Document-Term Matrix (DTM), CA acts as a multivariate dimension reduction technique that highlights latent associations between keywords and documents. By projecting terms onto a Cartesian plane (semantic map) defined by principal factor axes, this method allows for a visual synthesis of how specific linguistic clusters relate to the final regulatory decision.

3 Application and results

The study analyzed 294 assessment reports corresponding to 184 unique drugs. Descriptive statistics revealed a balanced distribution between successful and unsuccessful claims (56% approved vs. 44% not approved). The average report length is 854 words, with approved drugs featuring slightly more extensive documentation (860 words) compared to non-approved ones (845 words). Notably, the 'Added Following data cleaning and keyword coding, frequency analysis reveals that reports

associated with a “Not Approved” status are frequently characterized by the keyword term “indirect comparison” — a fundamental methodology in drug studies — as shown in Figure 1, which displays the twenty most frequent keywords by innovativeness status and illustrates how the structure of key terms is highly similar across the different categories

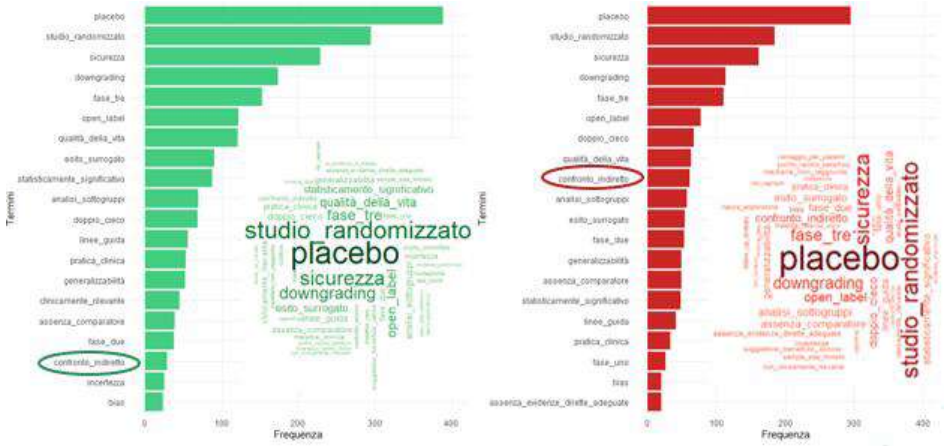

Figure 1: *Top Keyword frequency by Innovation approved (n=166; green), vs Innovation Not Approved (n=128; red) from 2016 to 2025.*

Semantic network analysis delineates distinct conceptual clusters, highlighting an interesting divergence in specific bigrams between categories. Within the 'Approved Innovation' sub-corpus, terms are tightly integrated around 'significant therapeutic benefit' and 'robust clinical evidence,' with a frequent recurrence of phrases such as 'currently available' and 'overall survival.' Conversely, the 'Not Approved' sub-corpus reveals weaker associations between clinical outcomes and therapeutic needs, focusing primarily on terms like 'clinical benefit' and 'assessable impact.' Topic Modeling (LDA) [2] results further clarify these trends, categorizing technical jargon into thematic topics—such as 'Study Design,' 'Clinical Outcomes,' and 'Therapeutic Treatment' — which are consistent with the three domains characterizing the reports.

Correspondence Analysis enables the creation of a semantic map of the most frequent keywords within a Cartesian plane, defined by the two main axes derived from the extraction of the first two principal components of a factor analysis based on keyword frequencies. Given that the study is in its initial phase, we hypothesize that these dimensions represent 'Study Solidity' and 'Uncertainty Level.'

4 Conclusions

This project demonstrates that text mining is a powerful tool for deciphering the complex language of pharmaceutical regulation and represents an innovative approach to analyzing innovativeness assessment forms. By examining AIFA reports, the study reveals how the conceptualization of innovation has evolved since 2017. Preliminary results highlight a broadly similar linguistic structure between approved

and rejected drugs; however, they also identify distinctive characteristics suggesting that 'Quality of Evidence' and 'Added Therapeutic Value' are the primary drivers of institutional discourse. Looking ahead, this methodological approach can be utilized to develop predictive tools for future drug evaluations, ensuring greater transparency and strategic alignment for stakeholders within the Italian healthcare landscape.

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A Multidimensional Decomposition of Tourism Rate Across Italian Provinces

Paolo Mariani and Mariangela Zenga

Abstract The traditional tourism rate, defined as the ratio of arrivals to the resident population, provides an incomplete picture of the socio-economic impacts on a territory. This study proposes an innovative multiplicative decomposition of the tourism rate into several indices, including pressure on tourism enterprises, employment intensity, and social externalities such as crime. By analyzing 105 Italian provinces using 2023 data, we reveal how identical tourism rates can stem from radically different structural drivers. The results highlight critical management challenges for high-vocation areas and provide a new framework for territorial resilience and public safety policies.

Key words: Tourism Pressure, Multiplicative Decomposition, Tourism Employment, Crime Rate, Italian Provinces, Economic Resilience.

1 Introduction

While tourism is a fundamental pillar of the Italian economy, its measurement has long relied on aggregate indicators that overlook the internal dynamics of the sector. The standard Tourism Rate (TR) fails to capture how visitor flows translate into actual pressure on local businesses, the workload of employees, or the increase in criminal activities. This paper addresses the research question: *How can the traditional tourism rate be decomposed to provide a more comprehensive and managerially relevant understanding of tourism pressure and social externalities at the territorial level?* The goal is to move beyond simple arrival numbers to map tourism on the local socio-economic enterprises. This research was carried out by the Bicocca applied Statistics Center.

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2 Methodology and results

The study adopts a multiplicative decomposition approach [1,2,3] applied to the 105 Italian provinces. Utilizing 2023 data from ISTAT, Movimprese, and the Excelsior Information System, the TR is broken down into two levels. The first level isolates the pressure on tourism enterprises and the density of these firms relative to the population. The second level further refines the analysis by introducing employment-related variables (arrivals per worker and firm size) and social indicators (crime rate per resident and an enterprise stability index). This multi-level structure allows for a granular comparison between provinces that might appear similar when looking only at total arrivals.

The empirical results demonstrate that Italy is characterized by extreme territorial heterogeneity. Northern provinces like Bolzano and Trento face high pressure due to massive demand relative to the number of available firms, suggesting a saturation of carrying capacity. Conversely, metropolitan provinces like Florence and Venice experience intense "pressure on employment," where the high volume of tourists per worker may threaten service quality and social sustainability. The analysis of social externalities confirms that higher tourism density often correlates with increased crime rates in large urban hubs. However, the proposed "Enterprise Stability Index" shows that some mature destinations possess a robust economic structure that can mitigate these negative effects, while other regions remain highly vulnerable.

3 Conclusions

A multidimensional assessment is essential for effective tourism governance. The proposed framework allows for the classification of provinces into distinct clusters enabling policymakers to move away from generic strategies. For destinations under labor stress, policies should focus on workforce support and seasonal management; for areas with high crime externalities, integrated security measures are paramount. Finally, this decomposition provides a strategic map to guide Italy toward a more sustainable and resilient tourism model that balances economic growth with social safety and labor welfare.

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A Multilayer Network Framework for the Identification of Functional Regions

Andrea Enrico Vurro, Andrea Mazzitelli and Giuseppe Espa

Abstract This study proposes an approach to delineate functional regions in Italy by generalising industrial districts, starting from the Local Labour Systems (LLS) defined by Istat (2011). Three forms of proximity between LLS are represented in a multilayer graph: geographic contiguity, productive similarity between firms, and collaborative ties elicited by network alliances, suitably filtered through the backbone analysis. On the aggregated graph, a community detection algorithm identifies contiguous and cohesive functional regions.

Key words: Labour Market Areas, Network Alliances, Graph Theory, Multilayer networks, Community Detection, Spatial Clustering, Backbone Analysis

1 Data and variables

The empirical analysis relies on a dataset combining territorial, firm-level and textual information. The geographical adjacence matrix is provided by the Italian LLS delineated by ISTAT in 2011. These 611 units are functional labour-market areas (LMAs) defined on commuting flows and internal self-containment, and are used as the basic geographical nodes of the model [1]. Their official shapefile supplies the geometry necessary to construct the geographical layer of the network.

Economic information is drawn from the universe of network alliances (NAs) registered with the Italian Chambers of Commerce, which document structured

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patterns of inter-firm cooperation. The initial dataset comprised over 7,500 networks; after excluding inactive units and filtering out records with missing or invalid geographic coordinates, the resulting dataset includes roughly 4,500 networks involving about 23,000 firms and 137,000 distinct locations. This integrated data set underpins the construction of the semantic and collaborative layers of the multilayer graph [2]: firms are grouped by NAs and their locations aggregated to LLS, so that edges capture the intensity of formal cooperation between labour systems, while network-level corporate-purpose texts provide the corpus for topic extraction and the measurement of functional similarity.

2 Methodology

In the empirical strategy, Italian LLS are modelled as territorial nodes of a multilayer network, where each layer encodes a distinct notion of proximity between places. The geographic layer is built from the 2011 ISTAT LLS shapefile by computing a binary contiguity matrix under the queen criterion: two LLSs are connected if their polygons share at least one boundary point, yielding a sparse graph that enforces spatial continuity in subsequent aggregations. The semantic layer captures functional similarity between territories by exploiting the corporate purposes of firms involved in NAs: the text of these purposes is aggregated at the level of each alliance, k latent topics θ_d are extracted using Latent Dirichlet Allocation, and the resulting topic-weight vectors are reallocated to LLSs according to firm locations, producing a bipartite LLS–topic graph that is projected into an LLS–LLS similarity network. The collaborative layer is constructed in an analogous way from a bipartite LLS–contract graph, in which an LLS is linked to all NAs hosting at least one of its firms, and the one-mode projection yields LLS–LLS edges weighted by the intensity of shared participation. These three graphs constitute the geographic, semantic and collaborative layers of the multilayer model.

2.1 Collaborative layer and semantic layer

The collaborative layer A_{collab} and the semantic layers A_{topic} are derived from bipartite graphs sharing the same territorial partition. LLSs are linked to NAs in the first case and to latent LDA-inferred topics in the second. In the semantic layer, document-level topic vectors θ_d, estimated by LDA, are first assigned to the LLSs hosting the corresponding firms. For each LLS i, a semantic profile is obtained by averaging the topic compositions of all associated documents, yielding an LLS–topic incidence matrix whose entries measure the relevance of each topic in each territory. Projecting this bipartite graph onto the LLS set ($P = BB$^⊤) produces a weighted LLS–LLS network in which edge weights quantify semantic similarity between territorial profiles. The collaborative layer is constructed analogously, by linking LLSs to contracts whenever at least one participating firm is located in the LLS; projection

onto the LLS set then defines edge weights that capture the intensity of institutionalised cooperation induced by joint participation in network agreements.

In both layers, dense bipartite projections are filtered using statistical backbone extraction [3]. The collaborative layer uses the Fixed Degree Sequence Model (FDSM), which exactly preserves LLS and contract degrees and yields a conservative backbone. The semantic layer uses the fixedfill null, which constrains only the total edge count and produces a more permissive, slightly denser backbone; edges are kept if significant at $\alpha = 0.10$.

2.2 Multilayer graph

The three adjacency matrices, A_{geo}, A_{topic} and A_{collab}, are aligned on the common set of LLSs, rescaled to make edge weights comparable, and the multilayer network is collapsed into a single weighted graph via a convex combination:

$$W = \alpha_{geo}A_{geo} + \alpha_{topic}A_{topic} + \alpha_{collab}A_{collab}$$

Consistent with the theoretical literature on industrial districts [4] and Tobler's laws, which emphasizes spatial concentration as the primary condition for agglomeration, the geographic layer is assigned a dominant weight α_{geo}=0.7, the semantic and collaborative layers receive weights α_{topic}=0.2 and α_{collab}=0.1, respectively. Preliminary experiments showed that lower geographic weights produced highly fragmented partitions, with many enclaves and non-contiguous regions.

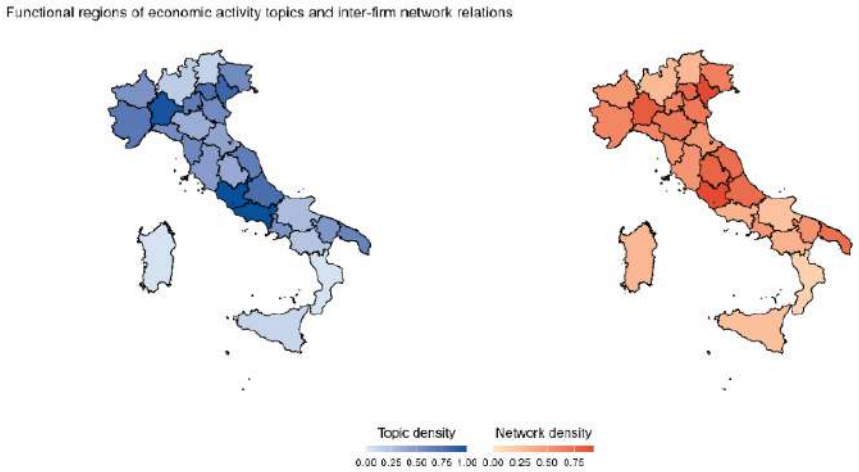

Figure 1: The scheme illustrates the aggregation into functional regions, representing the density of the projected subgraphs to visualise how LLS clusters vary in topic similarity and collaboration intensity.

Communities are detected on the aggregated graph W using the Leiden algorithm, with resolution ≈1.4 chosen to obtain a few dozen spatially contiguous regions without enclaves [5]. Partition quality is evaluated by Newman–Girvan modularity (≈0.07), which is low but expected for a nearly planar, geography-dominated multilayer

network; here modularity serves mainly as a descriptive statistic complementing geography-constrained regionalisation [6].

3 Results

The multilayer network applied to Italian LLS delineates 28 contiguous functional regions (Figure 1) that act as a higher-order territorial scale. Combining geographic contiguity, sectoral–semantic similarity and contractual inter-firm ties, the model yields a three-dimensional representation of territorial cohesion, clustering LLS that are at once neighbouring, specialised and interdependent. These regions are hybrid functional entities, defined by convergent production profiles and organised relations, revealing latent technological, logistical and knowledge-based affinities.

Some regions display high semantic cohesion but weak contractual ties, others are strongly structured by inter-firm alliances, and a subset combines comparable levels of semantic and collaborative density. These profiles show that the multilayer procedure captures heterogeneous mixes of production specialisation and organised cooperation. The multilayer architecture itself is modular and generalisable: additional proximity dimensions can be plugged in, making it suitable for clustering along unconventional, textual or relational dimensions that standard regionalisation procedures handle poorly. Within this architecture, backbone analysis is crucial. It statistically filters dense networks, removing noise, highlighting substantively meaningful ties and simplifying the multilayer graph, while providing a principled basis for metrics of relevance and robustness. The framework is nonetheless sensitive to hyperparameters: the weights assigned to the three layers and the resolution of the Leiden algorithm shape cluster size and morphology. Robustness therefore resides in the transparency and replicability of the analytical procedure rather than in the precise delineation of borders, so that national economic geography is recast as a system of multidimensional regions.

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A Multiple Discrete-Continuous Approach to Food Demand: Implications for Policy Evaluation

Beatrice Biondi and Mario Mazzocchi

Abstract Demand modeling is widely used to inform fiscal policy for frequently purchased goods such as food. We estimate a Multiple Discrete-Continuous Extreme Value (MDCEV) model on household scanner data, capturing both the discrete selection of food groups and the continuous choice of purchased quantities in a single framework that accommodates multiple discreteness. The estimated model yields interpretable behavioural parameters, such as category-specific satiation, allowing us to distinguish the marginal utility contribution across different food groups. We then apply the model to simulate a fiscal policy intended to promote more sustainable diets, and discuss the resulting behavioural responses in terms of substitution patterns and budget-constrained adjustments across food and drink categories.

Key words: Food demand, choice modelling, MDCEV model, household scanner data

1 Introduction and Motivation

Empirical demand models are central to fiscal-policy design because they support credible predictions of how consumers adjust to changes in prices and incomes. Fiscal instruments (taxes/subsidies) can shift consumption, but their effectiveness hinges on heterogeneous and context-dependent responses that standard representative-agent assumptions may miss.
The objective of food policies is distinct from other consumption policies: unlike

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e.g. alcohol or tobacco regulation, where the policymaker may ideally seek to drive consumption toward zero, food policies typically target specific food categories, such as High in Fats, Sugar and Salt (HFSS) products or high-emission foods. Therefore, changes in dietary composition and the associated within-basket substitution patterns become crucial.
Accordingly, evaluating food taxes requires separating changes in purchase incidence (extensive margin) from changes in purchased quantities conditional on buying (intensive margin), both on the targeted and not targeted food groups. This distinction is also distributionally relevant, as different households may react by reducing purchase frequency, moderating quantities, or substituting toward cheaper or untaxed alternatives.

High-frequency household scanner data are well-suited to studying these mechanisms because they track repeated purchase occasions and allow substitution patterns to be identified at granular category levels. At the same time, scanner data are sparse, with many zeros, creating methodological challenges for traditional continuous demand systems built for aggregate expenditure shares.

Conventional demand-system approaches (e.g., AIDS and its extensions) remain influential but are typically tailored to continuous expenditure data [1, 2]. Discrete-choice models handle zeros naturally, yet they often abstract from the continuous quantity decision that is essential for policy analysis. A unified discrete-continuous framework can reconcile these needs by jointly modeling category-level choice and conditional quantities within a single utility-maximizing structure.
We therefore adopt the Multiple Discrete-Continuous Extreme Value (MDCEV) model [3] for the estimation and simulation of food demand, which accommodates multiple discreteness and realistic basket choice. This structure is not only behaviourally-appropriate, but also returns interpretable behavioural parameters (e.g., category-specific satiation) that help explain substitution and reallocation under budget constraints. Because unobserved household tastes are important in food demand, we also formulate a practical adjustment that captures stable heterogeneity among household tastes.

2 Data

The empirical analysis relies on household scanner data on food and beverage purchases collected by YouGov CP Italy. The panel covers a representative sample of Italian households observed between January 2023 and April 2024. We use a balanced subsample of 3,954 households, which also reports variable-weight (non-barcoded) items (e.g., fresh produce, meat, fish). Purchases are aggregated at the household-week level for each food and non-alcoholic drink category. For each household-week-category record, the data report quantities (kg/litres), expenditure (EUR), number of items, and purchase channel (e.g., hypermarkets, supermarkets, local stores). The data include all food and drink purchases brought home made by the households in the panel (we exclude alcoholic beverages and bottled wa-

ter). Available covariates include household size, presence of children under 13, geographical area of residence, municipality size, and age and gender of the main food purchaser. For model assessment, 2023 data form the estimation sample, while January-April 2024 are considered for out-of-sample validation.

3 Methods

We model household i's weekly basket as a multiple continuous-discrete problem: consider K food categories, the household choose quantities $\mathbf{x}_{it} = (x_{1it}, \ldots, x_{Kit})$, at time t, in order to maximize:

$$U(\mathbf{x}_{it}) = \sum_{k=1}^{K} \frac{\gamma_k}{\alpha_k} \psi_{kit} \left[\left(\frac{x_{kit}}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right] s.t. \sum_{k=1}^{K} p_{kit} x_{kit} = B_{it} \tag{1}$$

Satiation (α_k) and translation ($\gamma_k > 0$) deliver diminishing marginal utility and allow corner solutions (multiple discreteness).
Baseline marginal utility is $\psi_{kit} = \exp(\beta_k' z_{kit} + \varepsilon_{kit})$, where z_{kit} includes prices and observed shifters and ε_{kit} captures idiosyncratic characteristics that impact the baseline utility of good k and is i.i.d. across alternatives Extreme-Value Type I, independent of $z_{kit} \forall k$, with a scale parameter of σ.
Let $V_{kit} = \beta_k' z_{kit}$ and scale σ; define expenditure $e^*_{kit} = p_{kit} x_{kit}$. For a chosen set S of M goods, the MDCEV probability has closed-form[1]. We estimate $\Theta = \{\alpha, \gamma_k, \beta_k, \sigma\}$ by maximum likelihood[2].
To capture persistent unobserved tastes in panel data, we implement a MDCEV model with residual unobserved effects via a modified demeaning step.
Specifically, we estimate $X^*_{ik} = \alpha_k + \mathbf{V}_i \beta_{1k}' + \mathbf{Z}_{ik} \beta_{2k}' + \mu_{ik}$, where X^*_{ik} is the total purchased volume (in kilograms or litres) of good k by household i during the full estimation period, and use $\hat{\mu}_{ik}$ as a household–category taste shifter in the baseline marginal utility equation.
We estimate and compare three specifications: a baseline MDCEV including observed covariates, an MDCEV-RUE variant that incorporates our fixed household effects to capture persistent unobserved heterogeneity, and a mixed MDCEV specification with random parameters.
We simulate a GHGE-weighted tax on animal-based foods [5]. Policy counterfactuals apply price changes, recompute predicted baskets under $\hat{\Theta}$, and summarize substitution and budget reallocation.

[1] $P(S, \mathbf{e}^*) = \sigma^{-(M-1)}(M-1)! \left[\prod_{k \in S} c_k\right] \left[\sum_{k \in S} c_k^{-1}\right] \frac{\prod_{k \in S} e^{V_k/\sigma}}{\left(\sum_{j=1}^{K} e^{V_j/\sigma}\right)^M}$, with $c_k = (1-\alpha_k)/(e^*_k + \gamma_k p_k)$

[2] We estimate the γ-profile, with a generic α, see [4]

4 Results and Conclusions

Estimation results deliver economically interpretable behavioural parameters for the three specifications. Estimated baseline preferences and covariate effects are highly significant, and households' tastes differ substantially, leading to meaningfully different purchase patterns and substitution responses across the sample. Across fit metrics, the MDCEV-RUE provides the best predictive performance while remaining the most parsimonious specification.

Under the emission-based tax, the model predicts strong targeted reductions for the most heavily taxed animal-based category, but also sizable substitutions toward untaxed staples. With a fixed food budget, substitution raises total quantities and generates a volume-driven rebound effect that can increase overall emissions despite reduced demand for taxed items. Allowing partial budget reallocation attenuates this mechanism: volume increases are small and emissions fall, consistent with cleaner substitution pathways. Overall, results underscore that policy evaluation hinges on jointly modelling extensive and intensive margins and on correctly representing budget constraints in counterfactuals.

Table 1 Models' fit and policy effects

	MDCEV	MMDCEV	MDCEV-RUE
Mean RMSE (out-of-sample)	1.45	1.46	1.35
Mean AUC (out-of-sample)	0.74	0.72	0.76
Policy impacts (MDCEV-RUE)			
Beef and lamb	quantity -26%; frequency -31%		
Total purchased volume	$+16\%$ (fixed food budget) $+2\%$ (food budget $+5\%$)		
Total emissions	$+5\%$ (fixed food budget) -0.3% (food budget $+5\%$)		

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A Spatial Difference-in-Differences Framework for Evaluating Place-Based Policies

Marusca De Castris and Guido Pellegrini

Abstract Moving beyond standard counterfactual approaches based on the Stable Unit Treatment Value Assumption (SUTVA), the paper adopts a spatial difference-in-differences (DiD) framework grounded in spatial econometrics. This approach enables the consistent estimation of direct, indirect, and total policy effects. The framework aligns with previous impact evaluations of European Cohesion Policy that account for spatial spillovers. We show that ignoring spatial interactions may lead to biased or underestimated estimates of treatment effects.

Key words: spatial DiD, spillovers, impact evaluation

1 Motivation

Place-based policy evaluations often assume that units are independent and unaffected by others' treatment status. This assumption—formalized as the Stable Unit Treatment Value Assumption (SUTVA)—underpins standard causal tools such as difference-in-differences (DiD), synthetic control methods (SCM), and matching estimators. While plausible for individual-level interventions, it is rarely credible in regional policies, where economic and institutional interactions across space are inherent to the policy design (Angelucci, 2016; Pellegrini and Cerqua, 2019).

In such contexts, policies may influence not only treated units but also nearby or economically connected untreated ones. Ignoring spillovers has two consequences: it yields an incomplete assessment by omitting indirect effects and may bias direct effect estimates by contaminating the control group (LeSage and Pace, 2009).

Recent methodological work shows that, under interference, policy impacts must be decomposed into direct effects on treated units and indirect (spillover) effects on

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exposed but untreated units. This literature extends the DiD framework by redefining treatment through exposure measures based on geography or economic proximity (Lasso Jaramillo, 2025). We distinguish three empirical cases and situate our previous analysis in the intermediate scenario, where spillovers affect only part of the control group and exposure can be proxied by distance. Our contribution is methodological and broadly applicable to policy evaluation under interference.

2 Counterfactual Framework with Spatial Interference

We distinguish three evaluation settings based on the nature and observability of spillovers (Celli et al., 2025).

In the benchmark case, the policy affects only treated units. Untreated units remain unaffected and provide valid counterfactuals. Under the parallel trends assumption, standard DiD identifies the Average Treatment Effect on the Treated (ATT). This framework underpins much of the traditional evaluation literature.

In the second case—common in applied settings—spillovers affect only a subset of untreated units, typically those geographically close or economically connected to treated areas. Interference can then be modelled through an exposure matrix that captures how treatment propagates across units, based on distance, contiguity, or network and market linkages. This structure distinguishes treated units, exposed untreated units, and unexposed controls. Under partial interference (Sobel, 2006), it is possible to identify and decompose direct effects on treated units, spillover effects on exposed controls, and total effects combining both (LeSage and Pace, 2009). Recent extensions of DiD operate in this framework by incorporating exposure measures or imputing counterfactual outcomes (Lasso Jaramillo, 2025). However, the specification of the exposure matrix is often ad hoc and not directly testable.

In the most challenging case, spillovers potentially affect all untreated units and the exposure structure is unknown. No valid control group exists, and standard control-based methods fail. Identification must instead rely on forecasting-based counterfactual approaches that exploit pre-treatment dynamics rather than cross-unit comparisons (Celli et al., 2025).

Most of the literature that explicitly accounts for spillovers focuses on the second setting, where interference is selective and can be proxied by geographic distance within an exposure matrix (e.g., De Castris, Di Gennaro, Pellegrini, 2023).

3 Potential Outcomes with Exposure

Building on Celli et al., (2025), let $D_i \in \{0,1\}$ denote treatment status. Let W be a spatial or network weights matrix capturing the intensity of interactions across units. Exposure to treated units is defined as:

$$E_i = \sum_{j \neq i} w_{ij} D_j \quad (1)$$

where w_{ij} typically declines with geographic distance or economic proximity.

The spatial weights matrix W plays the role of an exposure mapping in the sense of Sobel (2006), translating the treatment status of neighboring units into a continuous measure of potential interference.

Potential outcomes depend on both own treatment and exposure:

$$Y_{it}(d, e), d \in \{0,1\}, e \geq 0. \quad (2)$$

Observed outcomes satisfy:

$$Y_{it} = Y_{it}(D_i, E_i) \quad (3)$$

This framework extends the standard potential outcomes model by allowing treatment effects to spill over across units. To identify causal effects within this framework, we impose a set of standard conditions adapted to the presence of exposure (Lasso Jaramillo, 2025). In particular, treatment and exposure must be conditionally exogenous with respect to time-varying unobservables, outcome trends in the absence of treatment must evolve similarly across units conditional on exposure intensity, and units must not anticipate future treatment or spillovers. In addition, the chosen weights matrix must provide a consistent proxy for the underlying diffusion structure.

Under these conditions, direct and spillover effects are separately identified.

4 Difference-in-Differences with Spillovers

A typical example of the second case in our classification is the DiD model with spillovers. The empirical strategy combines DiD with spatial econometric techniques, often relying on a Spatial Durbin–type specification:

$$Y_{it} = \alpha_i + \lambda_t + \beta(D_i \times Post_t) + \theta(E_i \times Post_t) + X'_{it}\gamma + \varepsilon_{it} \quad (4)$$

where $\alpha_i$and λ_t are unit and time fixed effects, $Post_t = \mathbb{1}(t \geq t_0)$, β captures the direct policy effect, θ captures the spillover effect, X_{it} are time-varying controls.

The total effect for unit i is:

$$\mathrm{TE}_i = \beta + \theta E_i. \quad (5)$$

This decomposition shows that focusing only on β may yield an incomplete—or even misleading—assessment of policy effectiveness.

This empirical design has been applied to evaluate European regional policy over the 2007–2013 programming period, exploiting a multilevel structure with treatment assigned at the NUTS-2 level and outcomes observed at the NUTS-3 level (De Castris,

Di Gennaro, Pellegrini, 2023). The analysis reveals sizable positive spillover effects: regions neighbouring treated areas also benefited, particularly when both the region and its neighbours were recipients of Cohesion Policy funds. Findings corroborate recent evidence on spatial diffusion mechanisms associated with EU investments (Di Gennaro, Pellegrini, 2019; Ehrlich, Overman, 2020; Di Caro, Fratesi, 2022). The methodological framework illustrates how spatial DiD models provide a coherent extension of counterfactual evaluation techniques in settings characterized by interference.

5 Conclusions

This paper develops a spatial difference-in-differences framework to evaluate place-based policies in the presence of spillovers. By embedding an exposure mapping within the potential outcomes approach, we show how policy impacts can be decomposed into direct, indirect, and total effects.

Focusing on settings with localized interference, we clarify the assumptions required for identification and demonstrate that ignoring spatial interactions may lead to biased or incomplete estimates. Accounting explicitly for spillovers is therefore essential for credible policy evaluation in regional contexts.

Acknowledgements: This work has been supported by MIUR, grant number 2022XRHT8R - The SMILE project: Statistical Modelling and Inference for Living the Environment.

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A Sustainability Index for Water Transport and Sustainable Growth

Paolo Mazzocchi and Claudio Quintano

Abstract - In response to the intensifying climate and energy challenges, ports are progressively redefining their strategic role within the European economic system. No longer confined to transport and logistics functions, they are increasingly positioned as multifunctional energy nodes that contribute to decarbonisation in line with the European Green Deal, through the deployment of renewable energy, alternative fuels, and low-carbon technologies. The present study examines how water transport can simultaneously enhance its operational efficiency and serve as a catalyst for sustainable economic development.

Key words: energy transition, hydrogen, SMEs, Water transport.

1 Introduction

Water transport plays a central role in global trade and manufacturing supply chains. Within the European Union, commercial activity has become increasingly concentrated in major Northern European ports, which now function as global hubs strongly influenced by international trade volumes and global economic cycles rather than regional dynamics. Historically, ports have contributed to cost reductions and efficiency gains in logistics and energy distribution, serving as key nodes for several activities [5]. Nowadays, ports are undergoing profound structural changes driven by evolving trade patterns, vessel characteristics, maritime routes, and growing commitments to sustainable development [1]. In this context, ports retain a strategic role in the energy transition, particularly within the European economic system. The current paper addresses international and local planning and investment strategies related to the energy transition, with a focus on hydrogen as an innovative energy

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carrier, paying particular attention to the role of small and medium-sized enterprises (SMEs) in supporting sustainable growth. The study proposes a composite sustainability index for water transport, designed to capture the relationship between sustainability performance and growth dynamics. The analysis investigates whether the index is significantly associated with five key pillars: *policy and regulatory frameworks*, *supply chain performance*, *production characteristics*, *profitability*, and *environmental impact*. By identifying the relevant dimensions driving sustainable development in European water transport, the proposed framework aims to support managers and policymakers, offering a data-driven tool for policy assessment and strategic planning in this sector and related energy transitions. From a methodological perspective, the study adopts partial least squares structural equation modelling (PLS-SEM), a well-established statistical technique.

2 Literature review and data analysis

In an increasingly volatile global context, port resilience and adaptability have become central to development strategies, with growing emphasis on low-carbon and sustainable port models. The recent Ukraine conflict has increased costs and logistical constraints for trade flows, profoundly altering the European energy landscape and commerce that relies on water transportation. Water shipping sustains nations' economic growth; nevertheless, it represents a significant contributor to global carbon dioxide emissions (CO_2; [10]). Therefore, identifying the specific port operations that significantly impact CO_2 is essential to mitigate this impact and facilitate the transition to sustainable economic development models. All parties involved in transportation, including shippers, transport operators, freight forwarders, ports, energy producers, and policymakers, must come together, cooperate, and take action to decarbonise the sector [8]. To promote energy independence and sustainability, the sustainable production and utilisation of hydrogen within harbour regions represents a relevant initiative. Currently, renewable energy sources are essential for producing green hydrogen. The United Nations' Sustainable Development Goal 13, which aims to combat climate change, can be pursued by integrating nature-based solutions and other national policies [6]. Rezaei et al. [9] emphasised that logistics performance can be evaluated at various levels, ranging from firm-level analyses to country-level assessments. Consistent with this perspective, the World Bank developed the Logistics Performance Index (LPI), which adopts the country as the unit of analysis [2]. This choice is supported by the substantial impact that port systems within a country have on national economic performance. Following a perspective similar to Arvis et al. [2], this current paper proposes a model for evaluating latent constructs related to the sustainability index, and the performance of thirty-seven countries is explored. To investigate whether there is a significant relationship between the five aforementioned latent constructs and the *sustainability index* in the hydrogen usage, according to the European Commission's report [4], the relevance of SMEs in each European country is enhanced and recognised, and the use of their financial ratios has been involved [3]. Furthermore, the negative externalities of water transport represent

additional dimensions, which are manifested not only during navigation but also during docking in the port, affecting both the port and the surrounding area [8]. Specific NACE categories (strictly dependent on hydrogen-based technologies) were used as well, to determine a set of uniform and comparable indicators (almost 450,000 active SMEs were identified). This paper employs PLS-SEM, and Figure 1 illustrates the path diagram, which comprises five latent variables and fifteen manifest variables [7]. The table footnote lists their corresponding codes and descriptions.

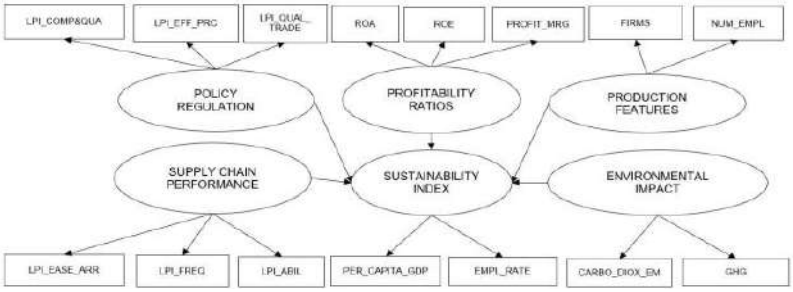

Figure 1 – Path diagram. Variables & their description: POLICY REGULATION: LPI_COMP&QUA-Competence and quality of logistics services; LPI_EFF_PRC- Efficiency of the customs clearance process; LPI_QUA TRADE- Quality of trade and transport-related infrastructure. SUPPLY CHAIN PERFORMANCE: LPI_EASE_ARR- Ease of arranging competitively priced shipments; LPI_ABIL - Ability to track and trace consignments; LPI_FREQ-frequency with which shipments reach the consignee within the scheduled or expected time. PRODUCTION FEATURES: FIRMS-Ratio between the number of SMEs & total firms for the NACE sectors involved; NUM_EMPL-Ratio between the n.of SMEs' employees & n. of employees for the NACE sectors involved. ENVIRONM. IMPACT: C02EMISS -CO_2 from water transport; GHG-Greenhouse gases. PROFITABILITY RATIOS: ROA-Return on Asset; ROE-Return on Equity; PROFIT_MRG-Profit Margin. SUSTAINABILITY INDEX: PER_CAPITA_GDP-GDP per capita, PPP; EMPL_RATE-Employment rate.

The assessments of construct homogeneity and one-dimensionality have been checked using Cronbach's alpha, D.G. rho and the first eigenvalue for each block. The Average Variance Extracted (AVE) confirms convergent validity. The cross-loadings indicate that the variance shared between a construct and its indicators exceeds that shared with other constructs, and the Heterotrait-Monotrait Ratio (HTMT) has also been verified, with results supporting strong discriminant validity. The main indices assessing the model's overall quality (such as the R^2 coefficient, communality, and the redundancy index) showed satisfactory results, along with additional robustness checks. The goodness-of-fit index (GoF) has an absolute value of 0.685 and a relative value of 0.545. Table 1 summarises the inner model estimations, presenting the path coefficients and their significance levels. The results show that two path coefficients - *policy regulation* and *production features* - are positive. However, only one exhibits a statistically significant relationship with the *sustainability index*, underscoring its crucial role in promoting sustainable outcomes.

Supply chain performance, *environmental impact,* and *profitability ratio* negatively impact the *sustainability index*. Among them, only *environmental impact* significantly affects the *sustainability index* negatively, which is an expected outcome. Indirect paths—stemming from potential causal relationships between manifest variables and latent constructs that are not directly linked but could influence the *sustainability index*—present non-significant impact coefficients.

Table 1: Inner estimations

Latent variable	Path coefficient	Standard error	p-value
POLICY REGULATION	1.613	0.583	0.009
SUPPLY CHAIN PERFORMANCE	-0.875	0.548	0.120
PRODUCTION FEATURES	0.058	0.134	0.668
ENVIRONMENTAL IMPACT	-0.234	0.137	0.099
PROFITABILITY RATIO	-0.117	0.138	0.402

3 Conclusions

Substantial relationships support statistical significance with *policy regulation* and *environmental impact*. The significance of *policy regulation* underscores how regulatory frameworks serve as a crucial enabler of sustainability-oriented investments. Overall, the findings confirm the pivotal role of public governance in guiding ports toward long-term sustainable transitions. Identifying key sustainability drivers can support policymakers and port managers in designing targeted growth engines.

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Advancing the Input-Output Framework in a Developing World

Giorgio Garau

Abstract This paper re-examines the Input–Output (I–O) framework through the complementary lenses of information production, redistribution analysis, and dynamic modelling. At the core of the discussion is the concept of a Statistical Information System (SIS), a theoretically grounded architecture designed to maintain coherence across increasingly heterogeneous data sources. The Total Factor Productivity Surplus (TFPS) approach, introduced by Emilio Fontela in 1989, is presented as a methodological foundation which—when embedded in Computable General Equilibrium (CGE) models and enhanced with artificial intelligence within an Advanced Decision Support System (ADSS)—enables the transformation of official statistics into forward-looking instruments that support sustainable and inclusive development.

Key words: SIS, TFPS, ADSS.

1 Introduction

The System of National Accounts (SNA) provides the conceptual framework for producing the statistical measures needed to analyse macroeconomic trends and ensure international comparability. The 2008 revision expanded the scope of national accounting by dedicating an entire chapter to satellite accounts, with applications to sectors such as tourism, health and the environment. The preliminary 2025 revision goes further by introducing Thematic and Extended Accounts, described as "flexible tools for increasing the visibility of key phenomena by bringing all relevant data together in one place while maintaining coherence with the SNA conceptual framework" (United Nations, 2025). These new instruments explicitly encourage the use of "additional external source data," opening the door to the integration of administrative records, platform-generated information and Big Data.

Within this evolving context, the role of I-O Tables (IOTs) becomes increasingly

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significant. Three dimensions are central to their renewed relevance. The first concerns information production: modern IOTs are built from Supply and Use Tables (SUTs), which define the architecture of the production system and enable the integration of external data sources. This integration is crucial for constructing thematic accounts and for measuring emerging industries such as renewable energy or the gig economy. The second dimension, concerns analysis. IOTs and their extensions support the evaluation of policy challenges ranging from carbon neutrality and international trade realignments to distributional effects of public interventions. The third dimension, concerns modelling. IOTs serve as the accounting backbone of several types of simulation models, particularly CGE models used for policy impact assessments and scenario analysis. The new SNA encourages the development of integrated modelling tools, including machine-learning-enhanced systems.

2 The Role of Statistical Information Systems (SIS)

The concept of a Statistical Information System (SIS) offers a unified perspective on these three dimensions. While the System of National Accounts (SNA) does not explicitly employ this term—using instead the notion of an "integrated system of national accounts"—the SIS framework is essential for connecting heterogeneous data sources within a consistent theoretical structure. More than simply a set of harmonized datasets, the SIS constitutes an architecture that aligns the production of information with analytical aims and modelling needs. The logic of the SIS becomes evident when using national accounts to support economic modelling. Any attempt to build a model—whether short-run or long-run—requires a clear representation of economic actors and their relationships through an entity–relationship (E/R) scheme. This structure enables the identification of where information is produced, consumed and transformed, thereby enabling the integration of data sources from censuses, administrative archives, firm-level information systems and digital platforms.

Input–Output Tables represent the simplest form of SIS-based modelling. The theoretical structure underlying IOTs is a short-run representation of production technology based on fixed technical coefficients, following the Leontief tradition. The degree of productive integration among sectors becomes a measure of the economy's exposure to exogenous shocks. Since modern IOTs are derived from SUTs, it is at the industry–product level that analysts must integrate external sources or adapt the standard framework to emerging sectors, as suggested in the recent handbook on digital SUTs (OCDE, 2022).

This initial representation can be improved in two ways: by extending the accounting structure or by enriching the economic theory underlying the model. From the accounting perspective, the Social Accounting Matrix (SAM) provides a more comprehensive representation of value creation and redistribution. Built from the income and expenditure accounts of the national accounts system, the SAM incorporates institutions such as households, government and the rest of the world. It is consistent with the Keynesian tradition and supports the calculation of Type II multipliers (Miller, R.E. and P. D. Blair, 2009), which incorporate induced effects—those arising from the additional production triggered by household consumption.

From the modelling perspective, the fixed-coefficient structure of the IOT serves as the foundation for long-run models based on flexible production functions. These models allow the study of exogenous policy shocks through their effects on relative prices and provide a representation of the economy suitable for long-term simulations. CGE models, econometric I-O models and dynamic stochastic general equilibrium (DSGE) variants all rely on the accounting foundations provided by IOTs and SAMs.

3 Analysis: From Production to Redistribution and Equity

Structural analysis based on I-O tables examines how production systems are organized and how inter-sectoral linkages shape economic behaviour. Metrics such as multipliers, backward and forward linkages, and structural decomposition enable analysts to assess how changes in final demand, technology or trade patterns affect output, employment and emissions (Dietzenbacher & Lahr, 2004). These tools also allow the identification of key sectors, the detection of structural shifts and the assessment of regional vulnerabilities.

This paper expands the traditional I-O approach by analysing the redistribution of surplus among economic actors. Building on Fontela's (1989) Total Factor Productivity Surplus (TFPS) model, productivity gains are treated as a balancing item at constant prices, capturing the effect of technical progress. Garau (2022) advanced this framework by introducing the concept of Purchasing Power Transfer (PPT), enabling the decomposition of total surplus into Optimal TFPS—representing efficiency gains under competitive conditions—and Market Surplus, which measures distortions arising from monopoly power or rent-seeking strategies.

The methodological contribution of this work lies in advocating a single-deflation approach combined with Törnqvist price indices, that ensures that real productivity gains are correctly identified and that redistribution channels can be traced with precision. The ability to distinguish genuine efficiency gains from speculative rents is crucial in times of global crisis, when exceptional market conditions can lead to price distortions that disguise transfers of purchasing power. Identifying Market Surplus enables policymakers to intervene in rent-seeking dynamics that hinder equitable benefit distribution. This analytical framework promotes systemic fairness by revealing the internal rules governing resource transfers, thereby ensuring that productivity spillovers benefit households, essential public services and socially vulnerable groups.

The integration of TFPS and PPT indicators within CGE models enables a new class of analyses wherein structural reforms, tax policies or industrial strategies can be evaluated in terms of their capacity to redistribute productivity gains toward social inclusion, human capital accumulation and long-term resilience. In this way, the I-O framework becomes not only a descriptive tool but also a normative instrument capable of guiding development policy.

4 Modelling: Dynamic Adjustments and AI-Driven Decision Support

The evolution of economic modelling is increasingly shaped by the emergence of dynamic, AI-powered decision-support tools. In this context, the Statistical Information System (SIS) serves as the architecture that integrates traditional data sources with administrative archives and Big Data. The Advanced Decision Support System (ADSS) represents the computational environment in which these diverse data sources are harmonized, analysed and transformed into actionable insights. Within an ADSS, artificial intelligence and machine learning constitute the analytical engine capable of processing large-scale data, detecting structural anomalies and identifying patterns not visible to traditional statistical techniques.

Moreover, the ADSS automates sophisticated quantitative methods such as discounted cash flow analysis, sensitivity analysis and Monte Carlo simulation. These procedures provide decision-makers with a probabilistic understanding of future scenarios, allowing for robust planning under conditions of uncertainty. CGE models enriched with AI-driven behavioural equations offer a flexible platform for evaluating the long-term sustainability of economic strategies, including those related to energy transitions, industrial policy and human capital investment.

In this integrated environment, statistics evolve from retrospective descriptions to forward-looking instruments for governance. The SIS provides the conceptual coherence; the ADSS provides the computational power; and CGE modelling provides the analytical structure to connect micro-level dynamics with macroeconomic outcomes.

5 Conclusion

The transition to SIS-based, dynamically modelled economic analysis is essential for capturing the complexities of modern economies. By integrating Big Data, administrative sources and traditional statistical methods within an AI-enhanced ADSS, the system of national accounts evolves into a proactive tool capable of guiding structural transformation. Future research should prioritize developing thematic frameworks for emerging sectors and integrating micro-level digital data with meso- and macroeconomic models in order to advance toward a unified theory of value creation.

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Agricultural Seasonality, Credit Access, and Food Elasticities in Nigeria

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Abstract This study examines the roles of agricultural seasonality and credit access in shaping food demand elasticities in Nigeria. Using data from the 2023–2024 General Household Survey, we estimate a Working–Leser model that allows income effects to vary by season and loan access. The findings indicate that households with access to credit exhibit lower income elasticities, especially during the harvest season, suggesting improved consumption smoothing when liquidity constraints are eased. Pronounced regional heterogeneity underscores the need to incorporate both spatial and seasonal factors in food demand analysis.

Key words: Agricultural seasonality; Food demand elasticities; Credit constraints; Working–Leser model; Household consumption; Nigeria.

1 Introduction

Understanding how household food demand responds to income fluctuations is central to the study of consumption dynamics in low-income settings. Elasticities derived from Engel curves provide a compliant measure of such responsiveness, capturing how households adjust food expenditure shares as their resources vary (Banks et al, 1997). Recent work has shown that these elasticities are highly sensitive to empirical conditions, such as measurement error, household heterogeneity,

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and temporal variation in income, highlighting the need for context-specific analysis (De Brauw and Herskowitz, 2021).

Nigeria offers an especially relevant case for this investigation. As Africa's most populous country, it exhibits substantial structural transformation, rapid urbanization, and persistent nutritional vulnerabilities, while recent panel evidence documents marked heterogeneity in dietary evolution and income variability (De Brauw and Herskowitz, 2021). Moreover, Nigeria's agricultural calendar creates predictable seasonal cycles that influence both consumption patterns and labor supply, given the substantial contribution of the agricultural sector on GDP (approximately 25%). Households typically face a pronounced *hungry season*, characterized by depleted liquidity and reduced food consumption before harvest (Fink et al, 2020).

Seasonality interacts closely with credit constraints, as households often rely on borrowing during liquidity-poor months. Evidence from rural Africa shows that easing hungry season liquidity restrictions affects both consumption smoothing and productive decisions, influencing food choices and income trajectories (Fink et al, 2020). In Nigeria, where formal credit is limited, loan access significantly shapes food Engel curves. In this paper, we integrate these insights to examine how food expenditure elasticities in Nigeria vary across income levels, seasons, loan access, and geographic contexts, drawing on high-frequency panel data to disentangle structural from seasonal components of household behavior.

2 Data and Empirical Model

We rely on the most recent wave of the General Household Survey–Panel 2023–2024, a nationally representative longitudinal survey implemented by the Nigerian National Bureau of Statistics. The panel covers approximately 5,000 households across all six geopolitical zones and is administered in two interviews: the post-planting round (July–September 2023) and the post-harvest round (January–March 2024). The household questionnaire provides rich information on demographics, food and non-food expenditure, access to credit and exposure to shocks, while the agricultural questionnaire includes detailed modules on land use, inputs, and plot-level harvests. This dual-round structure allows us to distinguish seasonal variation in consumption behavior, while information on loan uptake makes it possible to analyses how liquidity constraints interact with seasonal shocks.

To estimate income elasticities of food demand, we adopt the Working–Leser model (WL, Leser, 1963), a widely used specification for modeling household budget shares. Let y_{ht} denote the total equivalized consumption of household h with $h = 1,\dots,H$ at time t, with $t \in (harvest, planting)$, and w_{ht} denote the corresponding household food budget share. The WL fixed-effects model is specified as

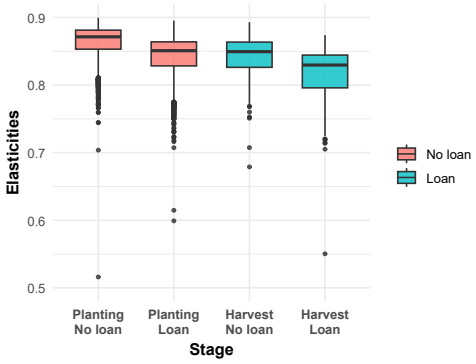
$$w_{ht} = \alpha + \alpha_t \times \alpha_{zone} + \alpha_{tl} \log(y_{ht}) + \sum_{k=1}^{K} \beta_k D_{kh} + \varepsilon_{ht}, \tag{1}$$

where α_{tl} is a varying slope that depends on time t and whether the household has received loans in the last year ($l = 0, 1$), D_{kh} is a vector of control variables. The interaction of time and zone fixed effects, $\alpha_t \times \alpha_{zone}$, controls for differences in price levels across geographic zones and over time (De Brauw and Herskowitz, 2021). This specification captures both the scale effects associated with changes in total consumption and heterogeneity across households in different structural conditions.

2.1 Results

The left-hand side table in Panel 1 reports the estimated coefficients from the fixed effects model with clustered standard errors. The interaction terms indicate systematic differences in total consumption responsiveness across agricultural periods and credit status. Differences in α_{lt}, $\forall l, t$, have been tested using an alternative model specification, and are found to be statistically different from zero. In both harvest and planting seasons, the coefficients on $\log(y)$ are negative and slightly larger in absolute value for loan households, suggesting a steeper reduction in food budget shares as total consumption increases in the case of access to credit. In addition, demographic controls and regional fixed effects reveal substantial spatial heterogeneity in food allocation patterns across Nigeria, with significant differences between geopolitical zones.

Variable	Est.	Std. Err.	p-value
Intercept	0.9110	0.0159	$< 0.001^{***}$
Not cultivating	-0.0491	0.0044	$< 0.001^{***}$
Residing in rural area	0.0755	0.0044	$< 0.001^{***}$
Zone: NE	-0.0061	0.0081	0.455
Zone: NW	-0.0274	0.0082	$< 0.001^{***}$
Zone: SE	-0.0391	0.0081	$< 0.001^{***}$
Zone: SS	-0.0115	0.0083	0.167
Zone: SW	-0.0229	0.0086	0.007^{**}
Planting season	-0.0511	0.0208	0.014^{*}
$\log(y)\times$ Harvest $\times$ No loan	-0.0907	0.0040	$< 0.001^{***}$
$\log(y)\times$ Harvest $\times$ Loan	-0.0964	0.0044	$< 0.001^{***}$
$\log(y)\times$ Planting $\times$ No loan	-0.0800	0.0038	$< 0.001^{***}$
$\log(y)\times$ Planting $\times$ Loan	-0.0875	0.0042	$< 0.001^{***}$
NE $\times$ Planting	0.0246	0.0116	0.033^{*}
NW $\times$ Planting	-0.0117	0.0116	0.317
SE $\times$ Planting	0.0068	0.0115	0.555
SS $\times$ Planting	-0.0125	0.0117	0.287
SW $\times$ Planting	-0.0181	0.0118	0.126



Panel 1 The left-hand table reports estimates from the Working–Leser model, while the right-hand figure presents boxplots of elasticities by category.

To further interpret the magnitude of these differences, we compute income elasticities of food expenditure from the estimated WL model as $\eta_{ht} = 1 + \frac{\alpha_{tl}}{\hat{w}_{ht}}$. The right-hand side figure in Panel 1 displays the distribution of elasticities across four groups defined by agricultural stage and credit status. Elasticities are consistently below one, confirming that food is a necessity across all groups. Nevertheless, systematic differences emerge: households with access to loans exhibit slightly lower median elasticities than non-loan households in both planting and harvest periods, indicating a weaker responsiveness of food expenditure to total expenditure

increases when liquidity constraints are relaxed. Seasonal differences are also evident, with marginally lower elasticities during the harvest stage, suggesting additional smoothing effects when total liquidity is higher and households face reduced income uncertainty and binding constraints. To test differences in elasticities and quantify uncertainty, we estimated the model in Equation (1) using a Bayesian approach, obtaining posterior distributions for each η_{ht}. Posterior means of quantile-based credible intervals by category are presented in Panel 2, with no overlap between those receiving loan and and those not in the planting season and only slight overlap in the harvest season.

Season	Loan	Credible interval (95%)	
		Lower bound	Upper bound
Planting	No	0.85	0.88
Planting	Yes	0.82	0.85
Harvest	No	0.83	0.86
Harvest	Yes	0.81	0.84

Panel 2 Posterior means by season and loan access of quantile-based credible intervals.

3 Further development

The elasticity estimates presented above provide a first descriptive attempt to assess how seasonality and credit constraints influence food demand in Nigeria. Furthermore, because loan uptake, labor allocation, and dietary adjustments vary across regions, accounting for the joint effects of loans and seasons at a finer geographical scale may be interesting in order to capture heterogeneity and relate it to ecological phenomena. This approach enables a detailed assessment of seasonal vulnerability, spatial variation in credit constraints, and the geographic distribution of consumption responses.

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AI-Driven Environmental Sentiment of EU Climate Benchmarks: The Hidden Volatility of Green Finance

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Abstract This paper investigates volatility dynamics, dependence structures, and downside risk interdependence in green equity markets, focusing on the Paris-Aligned Benchmark and Climate Transition Benchmark indices from 2017 to 2024. A GJR-GARCH-MIDAS model is used to decompose returns into short and long-term volatility components, with the latter driven by a latent Green-Adjusted Risk Factor. Dependence is modeled through a survival Gumbel copula, while downside risk spillovers are assessed using CoVaR measures. The results indicate that long-term volatility is influenced by sustainability-related uncertainty. Moreover, the copula-based CoVaR framework reveals strong bidirectional downside risk transmission between two indices, particularly during periods of systemic stress.

Key words: Green finance, Long-term volatilty, Copula, CoVaR

1 Introduction

In recent years, the increasing relevance of environmental and sustainability-related factors influenced financial markets and risk dynamics. This paper investigates the

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interaction between financial and environmental risks by combining volatility modeling and dependence analysis within an econometric framework. In Section 2 a Green-Adjusted Risk Factor (GARF) is obtained combining CBOE Volatility Index (VIX) and an inverted Green Attention Index (GAI) through an autoencoder model to represent aggregate systemic and environmental risk conditions. In Section 3, a GJR-GARCH-MIDAS model is computed to analyze the impact of the GARF low-frequency driver on long-term volatility of 16 equity green indices. Empirical results highlight that the GARF significantly explains the long-term volatility of FTSE EPRA Nareit Developed Europe ex UK Index (EXUK) and FTSE EPRA Nareit Developed Europe ex UK Green EU CTB Net Tax Index (FENGEX) assets. The Section 4 focuses on the dependence structure between EXUK and FENGEX using copula-based methods. By adopting a survival Gumbel copula, the study captures asymmetric and nonlinear dependence which is crucial for understanding systemic risk transmission. The CoVaR analysis further quantifies the spillover of downside risk from one asset to the other, revealing strong conditional dependence. Finally, the Section 5 concludes by summarizing the main findings.

2 Green-Adjusted Risk Factor

Alongside traditional volatility and uncertainty indicators, such as the VIX, there has been an interest in environmental sentiment measures or "green sentiment". A Green-Adjusted Risk Factor (GARF) is defined as an overall risk measure that takes into account the systemic volatility component and the "green" perception of market. The GARF is a latent indicator combining VIX and Green Attention Index (GAI) and to obtain it an autoencoder model, an unsupervised neural network that learns a low-dimensional latent representation by minimizing the reconstruction error, is computed. The GARF was obtained at weekly frequency, and employed as a low-frequency driver of long-term volatility in GJR-GARCH-MIDAS model.

3 GJR-GARCH-MIDAS: methodology and results

As in [4], let $r_{i,t}$ be the daily log-returns of the assets investigated on day i of period t that is the low-frequency period. The GARCH-MIDAS model assumes that the volatility of returns is made up of a short and a long-term component. The log-returns are expressed as follows:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\,\varepsilon_{i,t}, \qquad \forall i = 1,\ldots,N_t. \tag{1}$$

The short-run volatility ($g_{i,t}$) follows a GJR-GARCH (1,1) process as in [5]:

$$g_{i,t} = \left(1-\alpha-\beta-\frac{\gamma}{2}\right) + \left(\alpha+\gamma I_{(r_{i-1,t}<0)}\right)\frac{(r_{i-1,t})^2}{\tau_t} + \beta g_{i-1,t}, \tag{2}$$

where $I_{i-1,t} = 1$ if $r_{i-1,t} < 0$ and 0 otherwise. As in [3] the α assesses the impact of past news on actual volatility; the β assesses the persistence of volatility over time; the γ measures the additional impact on conditional volatility when the past return is negative. The stability condition is $\alpha + \beta + \frac{\gamma}{2} < 1$.

The long-run volatility (τ_t) evolves according to:

$$\tau_t = m + \theta \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{t-k}, \tag{3}$$

with θ that measures the impact of low-frequency variable on long-term component of volatility, ϕ_k is the Beta weighting function (see [2]), and X_t denoting the GARF variable at weekly frequency. In Table 1 are reported the results only for EXUK and FENGEX assets in which the GARF have an impact on long-term volatility from 2017 to 2024. The model, for the remaining 14 assets of MSCI, is not eligible.

Table 1 Results GJR-GARCH-MIDAS

Asset	μ	α	β	γ	m	θ	ω_2
EXUK	0.0127	0.0255*	0.9112***	0.0977***	0.4260*	0.9232**	8.7916
	(0.0227)	(0.0150)	(0.0194)	(0.0254)	(0.2673)	(0.4424)	(11.0657)
FENGEX	0.0230	0.0192	0.9160***	0.1045***	0.3944	0.7360**	10.4762
	(0.0234)	(0.0151)	(0.0175)	(0.0230)	(0.2806)	(0.4506)	(39.6683)

The impact of the low-frequency variable on long-term volatility (θ), provides crucial insights into the role of the latent GARF variable. The findings suggest that an increase in aggregate systemic risk for environmental topics, leads to higher long-term volatility levels, and it is shaped by a financial channel through which macroeconomic instability influence the persistence of volatility, and from an environmental sentiment channel, through which collective attention to green issues affects investor expectations, portfolio allocation, and risk pricing.

4 Copula and CoVaR: methodology and results

Copula functions provide a flexible framework to model dependencies by separating the marginal behavior of each variable from their joint dependence structure. This is important when analyzing systemic risk and conditional risk measures such as the Conditional Value-at-Risk (CoVaR).

The concept of copula functions is based on Sklar's theorem presented in [6]. For a p-dimensional random vector $\mathbf{x} = (x_1, x_2, \ldots, x_p)^T$ with marginal distribution functions $F_1, F_2, \ldots, F_p$, the joint distribution function F can be expressed through a copula function $C(\cdot)$ as:

$$F(\mathbf{x}) = C(F_1(x_1), F_2(x_2), \ldots, F_p(x_p)) \tag{4}$$

Only the pair EXUK-FENGEX is considered due to its statistical significance in the parameters for GJR-GARCH-MIDAS model, and transformed its standardized residuals into cumulative distribution function. The survival Gumbel copula was chosen as the best suited among all the possible static bivariate copulas analyzed through the AIC criterion.

The CoVaR following [1] is computed to quantify the extent to which stress in one asset propagates to the rest of the system. The backtesting results reinforce the statistical reliability of the copula-based CoVaR framework. For the pair the empirical conditional breach frequencies are close to the nominal 5% conditional probability benchmark ($\cong 0.49$ and $\cong 0.46$, respectively), implying that the model is well calibrated under a static dependence assumption.

5 Conclusion

The results show that long-term volatility driven by the Green-Adjusted Risk Factor captures the impact of sustainability-related uncertainty on green equity markets. Significant interconnections emerge between the EXUK and FENGEX indices in both long-term volatility dynamics and conditional downside risk. The relevance of the GARF component highlights how environmental policy uncertainty and sustainability-related investor sentiment can amplify financial instability. The CoVaR analysis provides evidence of risk transmission, with adverse shocks in one asset propagating conditional losses to the other. Backtesting confirms the robustness of the copula-based CoVaR framework, with empirical conditional breach frequencies close to the nominal 5% benchmark. The framework offers an effective early-warning tool for policymakers and financial supervisors, and suggest that green assets remain exposed to systemic downturns during periods of macroeconomic stress.

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Aligning Pay with Purpose: Do ESG-Linked Executive Compensation Policies Matter?

Sergio Longobardi, Carla Morrone, Giacomo Gotti and Marco Venuti

Abstract: This study examines how executive compensation structures affect firms' sustainability performance in Europe. Using panel data on 2,176 listed companies over the period 2018–2023 and Fixed Effects and Correlated Random Effects models (CRE), it compares firms adopting ESG-linked compensation schemes with those relying solely on financial incentives or lacking incentive policies altogether. The results show that the absence of structured compensation or the exclusive use of financial-based incentives is associated with significantly lower ESG scores. These findings underscore the importance of integrating ESG criteria into executive compensation as a key governance mechanism to enhance corporate sustainability performance.

Key words: ESG performance; Executive compensation; Agency theory; Stakeholder theory; Corporate governance

1 Introduction and theoretical background

In 2015, the United Nations adopted the 2030 Agenda, a global action plan for sustainable development structured around 17 Sustainable Development Goals (SDGs) and 169 targets that cover environmental, social, economic, and institutional dimensions. Achieving these goals requires the active engagement of all societal actors, including firms, public institutions, policymakers, and civil society. Prior

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research highlights the strong alignment between SDGs and environmental, social, and governance (ESG) factors, which together operationalize the three pillars of sustainability and reflect the Brundtland definition of sustainable development (Berenberg, 2018; Sætra, 2021).

In recent years, academic debate has increasingly focused on ESG issues and firms' sustainability performance. A key governance mechanism in this context is the use of executive compensation linked to ESG or sustainability metrics, which signals corporate commitment and responds to regulatory and societal pressures (Veltri et al., 2025). Although prior studies generally report a positive relationship between ESG-linked pay and ESG performance, evidence remains limited and sometimes suggests symbolic rather than substantive effects, particularly in Europe. Addressing this gap, the present study examines the differential impact of financial-based versus ESG-based executive compensation on firms' ESG outcomes, using panel data from 2,176 European listed companies over the 2018–2023 period, a phase characterized by increasing sustainability reporting regulation.

2 Data and methods

The econometric analysis employs a panel data approach to estimate the impact of executive compensation policies on firms' sustainability performance. The dataset comprises 2,176 companies retrieved from Refinitiv, a widely used financial database that provides standardized and internationally comparable firm-level information on ESG metrics, governance structures, and executive compensation, and observed over the period 2018–2023. The dependent variable, ESG_{it}, represents the aggregate ESG score of firm *i* in year *t*, which captures its environmental, social, and governance performance. The main explanatory variables are two dummy indicators generated to capture different configurations of executive compensation policies: D_{it}^{no} takes the value 1 if the firm does not implement any executive compensation policy, while D_{it}^{perf} takes the value 1 if the firm's compensation schemes are solely linked to financial performance indicators. The reference category for both dummies includes firms that adopt compensation policies tied to both financial and ESG performance. The model includes a set of control variables related to several aspects of the firms: governance and transparency ($CSRreport_{it}$, $CEOdual_{it}$), audit committee characteristics ($Auditindep_{it}$), and financial structure variables (ln $Assets_{it}$, $DebtEquit_{it}$). The baseline specification is a Fixed Effects (FE) model:

$$ESG_{it} = \alpha_i + \beta_1 D_{it}^{no} + \beta_2 D_{it}^{perf} + \gamma' Z_{it} + \delta_t + \varepsilon_{it} \quad (1)$$

where α_i captures firm-specific unobserved heterogeneity, δ_t denotes year fixed effects, and Z_{it} is the vector of control variables. The FE specification controls for unobserved heterogeneity across firms and across time. To account for the possibility that changes in compensation structures affect sustainability performance with a temporal lag, a dynamic version of the model is estimated by including the one-period

lag of the two compensation dummies. Since Fixed Effects models cannot estimate the impact of time-invariant variables (such as industry sector), an alternative specification is estimated using a Correlated Random Effects (CRE) model following Mundlak (1978). This approach introduces the firm-specific means of the time-varying regressors ($\bar{X}_i$) into the specification of random-effects, modelling the correlation between the unobserved individual effects and the explanatory variables:

$$ESG_{it} = \alpha + \beta_1 D_{it}^{no} + \beta_2 D_{it}^{p} + \gamma' Z_{it} + \theta_1 \bar{D}_i^{no} + \theta_2 \bar{D}_i^{p} + \theta' \bar{Z}_i + \phi_S + \pi_1 Pl + \pi_2 St + \delta_t + \mu_i + \varepsilon_{it} \quad (2)$$

where *Pl* and *St* are time-invariant dummy variables equal to one if the firm operates in a polluting industry and if it is included in the STOXX 600 index. In addition, ϕ_S is a vector of dummies to control for the economic sector of activities and μ_i is the idiosyncratic random component. This formulation enables the decomposition of the total effect into a *within-firm* component (representing temporal variation) and a between-firm component (reflecting cross-sectional structural differences). A lagged version of the CRE model is also estimated to capture delayed effects.

3 Results and discussion

Across all specifications (table 1), the findings are highly consistent, confirming the central role of incentive structures in shaping sustainability outcomes. The absence of a structured executive compensation policy is associated with a substantial and highly significant reduction in ESG performance. Firms without an incentive scheme score, on average, between 7.5 and 7.8 ESG points less than those adopting systems that link financial and ESG objectives. Firms relying exclusively on financial-performance-based compensation also underperform in ESG terms, with scores approximately 2.7 to 2.8 points lower. When lagged effects are considered, these relationships remain statistically significant but attenuated in magnitude, suggesting that the impact of compensation design is strongest contemporaneously, while its persistence over time is weaker yet still observable. From an agency perspective, ESG-linked incentives help align managerial actions with long-term sustainability goals. From a stakeholder perspective, the adoption of ESG-based compensation signals responsiveness to stakeholder expectations and regulatory pressures, ultimately leading to improved ESG ratings. The publication of CSR or sustainability reports shows a strong positive association with ESG performance, highlighting the importance of transparency and accountability. CEO duality is negatively correlated with ESG scores, indicating that power concentration may hinder governance effectiveness. In contrast, audit committee independence has a positive and significant effect, emphasising the role of oversight mechanisms in sustainability governance. Firm size has a positive impact on ESG performance, whereas higher leverage is associated with lower ESG scores, suggesting that financial constraints limit sustainability investments.

Table 1: Results of the panel estimation

Variable	Mod. 1 (FE)	Mod.2 (FE lagged)	Mod. 3 (Mundlak)	Mod.4 (Mundlak lagged)
Absence of compensation policy	-7.493***	-3.521***	-7.761***	-3.607***
Compensation only linked to performance	-2.764***	-1.274***	-2.843***	-1.251***
CSR_report	9.440***	9.355***	9.486***	9.210***
CEO_duality	-0.995**	-0.952**	-1.046**	-1.100**
audit_independ	0.067***	0.0668***	0.068***	0.068***
ln_assets	2.740***	2.735***	2.727***	2.597***
debt_equit	-0.013**	-0.009**	-0.0130**	-0.009*
Polluting sector (time invariant)	-	-	-2.981***	-2.893***
STOXX600 (time invariant)	-	-	6.200***	5.970***
Constant	-20.901**	-19.36*	-58.94***	-54.44***
Time dummies	*yes*	*yes*	*yes*	*yes*
Sectoral dummies (time invariant)	-	-	*yes*	*yes*
N	11,049	8,974	10,750	8,733

* p<0.10; ** p<0.05; *** p<0.01

Note: For the sake of simplicity, coefficients of the firm-level means are omitted from the table.

Time-invariant variables further reveal that firms in polluting sectors exhibit lower ESG performance, whereas inclusion in the STOXX 600 index is associated with significantly higher ESG scores, reflecting greater market scrutiny and institutional pressure. Overall, the results confirm that integrating ESG criteria into executive compensation represents a powerful governance tool for enhancing corporate sustainability performance, with effects that are both significant and robust across model specifications.

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An Age–Period Quantile Approach for Mortality Rates Forecast

Vito Manduano and Andrea Nigri

Abstract Mortality modelling typically focuses on conditional mean or median trends, overlooking heterogeneity and tail behavior. We propose an Age-Period quantile regression framework, estimated to describe and forecast, through auto-ARIMA, the mortality rates in Italian female conditional distribution (age 30–89, 1985–2015), avoiding the intrinsic identifiability problem of Age Period Cohort models.

Key words: Mortality, Age–Period, Quantile regression, ARIMA forecasting, Back-testing

1 Introduction

The steady increase in life expectancy has led to major achievements in demography, but it has also raised important actuarial and policy concerns. To understand the mortality dynamics underlying this process, we rely on statistical mortality models that provide a structured description of age-specific patterns, temporal dynamics, and the basis for forecasting longevity risk. Specifically, we apply an Age–Period (AP) quantile regression to log mortality rates for Italian females (by age 30-89, over a time period 1985–2015). The age component captures the systematic evolution of mortality risk over the life course, while the period component reflects contemporaneous shocks and innovations (e.g. pandemics, economic crises, and medical progress) affecting multiple age groups simultaneously.

The motivation for this approach lies in the adoption of the AP framework, which avoids the identification problems of Age–Period–Cohort models arising from the linear dependence between age, period, and cohort, while maintaining interpretable and predictive relevance [1]. In addition,

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quantile regression provides a more robust alternative to mean-based models, allowing distributional insight and reduced sensitivity to outliers [3] without imposing excessive constraints [2].

Forecasting is performed by applying an automatic ARIMA model to the estimated period effects. A simple back-testing scheme is implemented by separating in-sample estimation from out-of-sample forecast evaluation.We also provide a simple back-testing design separating in-sample fit and out-of-sample forecast evaluation.

2 Data and Notation

Let $a \in \{1,\dots,A\}$ denote single-year ages and $t \in \{1,\dots,T\}$ denote calendar years. Let $m_{a,t}$ be the central death rate at age a and year t. In continuous time, the force of mortality $\mu(x,t)$ represents the instantaneous risk of death at exact age x and time t [4]. Under standard assumptions, $m_{a,t}$ approximates the average of $\mu(x,t)$ over a one-year age interval, motivating modeling on central rates in period life tables. We work with the following outcome

$$y_{a,t} = \log(m_{a,t}), \tag{1}$$

The empirical application uses Italian female period life table data (ages 30–89) over 1985–2015 from the Human Mortality Database HMD.

3 Age–Period quantile regression

For a fixed quantile level $\tau \in (0,1)$, we specify an additive AP quantile model for $y_{a,t}$:

$$Q_{y_{a,t}}(\tau \mid a,t) = \mu(\tau) + \alpha_a(\tau) + \beta_t(\tau), \tag{2}$$

where $\alpha_a(\tau)$ is the age effect and $\beta_t(\tau)$ is the period effect at quantile τ. The intercept $\mu(\tau)$ absorbs the overall level at quantile τ.

Model (2) is identified by imposing standard constraints such as sum-to-zero on age and period effects:

$$\sum_{a=1}^{A} \alpha_a(\tau) = 0, \qquad \sum_{t=1}^{T} \beta_t(\tau) = 0. \tag{3}$$

In practice, we implement these constraints via sum contrasts in the design matrix, yielding an interpretable decomposition in which $\alpha_a(\tau)$ and $\beta_t(\tau)$ represent deviations around the overall level. Quantile regression estimates parameters by minimizing the check loss [3]:

$$\rho_\tau(u) = u\,(\tau - \mathbf{1}\{u < 0\})\,. \tag{4}$$

For each τ, we estimate $(\mu(\tau), \alpha(\tau), \beta(\tau))$ by solving

$$(\widehat{\mu}(\tau), \widehat{\alpha}(\tau), \widehat{\beta}(\tau)) = \arg\min_{\mu,\alpha,\beta} \sum_{a,t} \rho_\tau(y_{a,t} - \mu - \alpha_a - \beta_t) \quad \text{s.t. (3).} \tag{5}$$

Estimating multiple quantiles $(0.1, 0.5, 0.9)$ yields distributional information: differences between $\widehat{\beta}_t(0.9)$ and $\widehat{\beta}_t(0.1)$, for instance, can flag years where the upper tail of log-rates shifts more than the lower tail, consistent with shock-driven dispersion or heterogeneous impacts across ages.

3.1 Forecasting and Back-testing

The AP structure naturally supports forecasting by extrapolating the period component. After estimating $\widehat{\beta}_t(\tau)$ on a training window, we treat it as an uni-variate time series and forecast it using an automatic ARIMA specification:

$$\widehat{\beta}_t(\tau) \xrightarrow{\text{auto-ARIMA}} \widehat{\beta}_{t+h|t}(\tau), \quad h = 1, \ldots, H. \tag{6}$$

We then reconstruct quantile forecasts for log-rates and rates by age:

$$\widehat{Q}_{y_{a,t+h}}(\tau) = \widehat{\mu}(\tau) + \widehat{\alpha}_a(\tau) + \widehat{\beta}_{t+h|t}(\tau), \tag{7}$$

$$\widehat{Q}_{m_{a,t+h}}(\tau) = \exp\Big(\widehat{Q}_{y_{a,t+h}}(\tau)\Big). \tag{8}$$

This "AP + time-series period" approach mirrors standard practice in mortality forecasting, where the temporal driver is modeled and extrapolated separately (e.g., in the spirit of time-series treatment of period indices in classic models), while retaining the robustness and distributional insight of quantile estimation.

4 Results

We perform a simple train/test split at year $t^\star$: years $\leq t^\star$ are used for estimation (in-sample fit), and years $> t^\star$ are held out for out-of-sample forecasting. Let $\widehat{q}_{a,t}(\tau)$ denote the fitted/forecast quantile of $y_{a,t}$. We report MAE and RMSE on the log scale:

$$\text{MAE}(\tau) = \frac{1}{N}\sum |y_{a,t} - \widehat{q}_{a,t}(\tau)|, \qquad \text{RMSE}(\tau) = \sqrt{\frac{1}{N}\sum (y_{a,t} - \widehat{q}_{a,t}(\tau))^2}, \tag{9}$$

computed separately for in-sample and out-of-sample periods. As an additional diagnostic for quantile adequacy, calibration can be assessed via the empirical frequency $\text{P}\big(y_{a,t} \leq \widehat{q}_{a,t}(\tau)\big)$ which should be close to τ under correct specification.

This section summarizes the main empirical findings for Italian female mortality. The estimation is performed for $\tau \in \{0.1, 0.5, 0.9\}$ on $y_{a,t} = \log(m_{a,t})$. The training window is 1985–$t^\star$, and the out-of-sample window is $t^\star$+1–2015. The period index $\widehat{\beta}_t(\tau)$ is forecast using automatic ARIMA and then mapped back to age-specific quantile forecasts. Figure 1 shows observed mortality rates and fitted/forecast quantiles for selected ages, with a vertical line separating in-sample fit and out-of-sample forecast. The multi-quantile bands provide an immediate visual check of dispersion and systematic misfit, and they are useful for communicating forecast uncertainty without relying on strong parametric distributional assumptions.In order to test model accuracy, Table1 reports MAE and RMSE for each quantile, separately for in-sample and out-of-sample periods. However, tail quantiles (0.1 and 0.9) are harder to forecast than median, but they can reveal where prediction errors are concentrated (upper/lower tail) and whether forecast bands remain well calibrated.

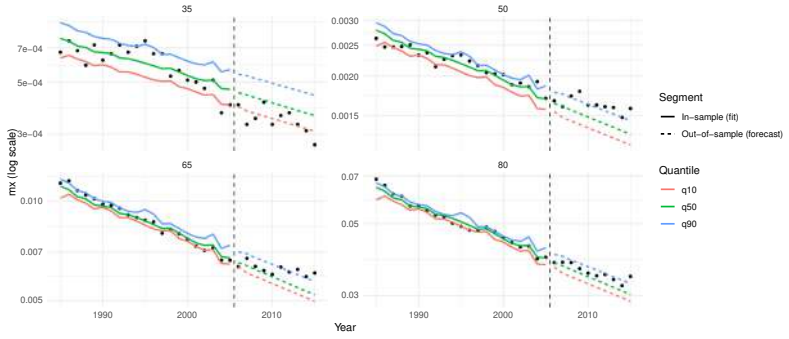

Fig. 1 Observed vs AP-QR fitted/forecast (auto ARIMA on period effect): observed $m_{a,t}$ (points) and fitted/forecast quantiles (lines) for selected ages. The vertical line marks the train/test split.

Table 1 Backtesting grid on log-rates $y = \log(m)$: MAE and RMSE by quantile and sample segment.

	In-sample (fit)		Out-of-sample (forecast)	
Quantile	MAE	RMSE	MAE	RMSE
$q_{0.10}$	0.0711	0.1078	0.1271	0.1453
$q_{0.50}$	0.0446	0.0706	0.0772	0.0989
$q_{0.90}$	0.0805	0.1249	0.1068	0.1724

5 Discussion and conclusions

We proposed an Age period quantile framework applied to mortality rates in order to highlight the distributional tail behavior, supporting natural prediction band (10-90%) and robust estimates to outliers. This allowed us to avoid the APC interpretation issues and directly impute the results to age profiles and temporal evolution, two main stable signals. Forecasting conducted through auto-ARIMA, reconstructed age-specific quantile while back-testing metrics (MAE,RAE), gives us transparent diagnostics. Future work should consider joint modeling of multiple quantile with non-crossing constraints, exposure-weighted estimation when deaths and exposures are available.

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Archetypal Logistic Regression for Response Propensity Estimation in Business Surveys

Alessandro La Rocca

Abstract This study proposes a novel methodology for estimating response propensity in business surveys by integrating Archetypal Analysis into a Logistic regression framework. Archetypal Analysis extracts a set of extreme behavioral profiles based on firms' structural characteristics, and each unit is represented by a vector of membership coefficients describing its position within the archetypal simplex. These coefficients are then used as regressors in an Archetype-Informed Logistic model, allowing response propensity to be predicted as a smooth function of proximity to the behavioral archetypes. Its performance is empirically evaluated against two, benchmark techniques, a standard Logistic Regression and a Random Forest classifier highlighting the potential of archetypal features to enhance prediction while preserving analytical transparency.

Key words: Business survey, Response propensity, Archetipal analysis, Logistic models, Nonrespons bias.

1 Archetypal Analysis

Archetypal analysis is a multivariate data decomposition technique that represents each observation as a convex combination of archetypes, which are themselves convex combinations of real data points. The method aims to identify a small number of extreme types archetypes located on the boundary of the data cloud, so that each observation can be approximated as a convex mixture of these idealized profiles. Unlike principal component analysis, which seeks directions explaining maximum variance, archetypal analysis focuses on finding pure or ideal cases that capture the fundamental behavioural tendencies within the data. Formally [1], given $x_{1,\dots,}x_n \in \mathbb{R}^m$ the goal is to find p archetypes $z_1 \dots z_p$ that minimize:

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$$\mathrm{RSS} = \sum_{i=1}^{n} \left\| x_i - \sum_{k=1}^{p} \alpha_{ik} z_k \right\|^2 \tag{1.1}$$

subject to the constraints:

- $\alpha_{ik} \geq 0$ per $i = 1, \ldots, n$, $k = 1, \ldots, p$
- $\sum_{k=1}^{p} \alpha_{ik} = 1$ per $= 1, \ldots, n$
- $\beta_{kj} \geq 0$ per $k = 1, \ldots, p$, $j = 1, \ldots, n$
- $\sum_{j=1}^{n} \beta_{kj} = 1$ per $k = 1, \ldots, p$

The vectors z_k are the the archetypes. The solution therefore involves finding the matrices α and ß that minimize the RSS subject to the above constraints. While this problem could, in theory, be solved using a constrained nonlinear least squares algorithm, such an approach becomes computationally infeasible even for moderately sized datasets. Instead, Cutler and Breiman proposed an alternating constrained least squares (CLS) algorithm, which iteratively estimates the two matrices until convergence. Many methods are available for solving constrained least squares (CLS) problems.

The method used to develop and test the algorithm is a penalized version of the non-negative least squares (NNLS) algorithm proposed by Lawson and Hanson [2].

2 Estimating Response Propensity in Business Census

Estimating response propensities in business surveys is essential for diagnosing and correcting potential nonresponse bias. Traditional models, such as Logistic Regression or Random Forest, provide individual level predictions but may struggle to capture latent behavioral structures underlying enterprises' response tendencies. To address this limitation, we introduce a modelling framework in which Archetypal Analysis (AA) is used not directly to compute propensities, but to derive a set of low-dimensional and interpretable regressors. The α matrix (α_{ik}) summarizes how closely each enterprise resembles each archetypal behavioral pattern. Rather than computing an archetype specific response rate and combining it through the α weights, we use these coefficients as regressors in a logistic regression model for the response indicator Y_i:

$$P(Y_i = 1) = Logit^{-1}\left(\gamma_0 + \sum_{k=1}^{K} \gamma_k \alpha_{ik}\right) \tag{2.1}$$

This archetype driven logistic model preserves the interpretability of AA, since coefficients γ_k quantify how proximity to each archetype affects the log odds of response. The estimated propensity for enterprise i is then:

$$\hat{p}_i^{(\alpha - Logit)} = Logit^{-1}\left(\hat{\gamma}_0 + \sum_{k=1}^{K} \hat{\gamma}_k \alpha_{ik}\right) \tag{2.2}$$

This approach offers two advantages. First, it produces fully continuous and model-based propensities, unlike discrete archetype averages. Second, it introduces an interpretable low-dimensional representation of enterprises' behavioral profiles, enhancing parsimony and robustness relative to high dimensional covariate models.

To assess predictive performance, the archetypal logit (3.1) is compared with a standard Logistic Regression based on survey covariates and a Random Forest classifier. Evaluation metrics include AUC and decile-based calibration plots.

3 Summary Results and Key Finding

In our experiment, we compared three modelling strategies for estimating response propensity sample component of the 2022 Istat Permanent Business Census [3]: an Archetype-Informed Logistic Regression model, a standard Logistic Regression, and a Random Forest classifier.

For the Archetype-Informed Logit, we first applied Archetypal Analysis to the structural covariates, obtaining for each unit a vector of membership coefficients α_{ik} with $K = 3$ archetypes. The α_{ik} coefficients were incorporated directly as regressors in a logistic specification. The response propensity for unit i is therefore:

$$p_i = P(y_i = 1 \mid \alpha_i)=(1 + exp[-(\gamma_0 + \gamma_1\alpha_{i1} + \gamma_{12}\alpha_{i2} + \gamma_{13}\alpha_{i3})])^{-1} \quad (3.1)$$

In this formulation, the coefficients γ_k quantify how proximity to each archetype influences the log-odds of responding, while the vector α_i summarises each firm's behavioural position in a low-dimensional and economically interpretable simplex. After estimating the three models, units were ranked by predicted propensity and grouped into deciles. Observed response rates were computed within each decile to evaluate discriminative ability. Figure 1 displays the resulting patterns. The Archetype-Informed Logit (solid line) exhibits a clear and coherent upward trend, particularly from decile 7 onward. Although the separation is smoother than that achieved by purely covariate-based models, the archetypal regressors succeed in capturing a latent behavioural progression: firms closer to certain archetypes are consistently more likely to respond. Unlike standard Logistic Regression (dashed line), which produces a monotonic but less behaviourally interpretable gradient, the archetypal specification leverages structural heterogeneity in a principled and dimension-reduced way.

Compared with Random Forest (dotted line), which shows an abrupt jump in the top deciles due to its ability to detect complex nonlinearities, the Archetype-Informed Logit offers a more stable and explainable stratification. Its smoother profile in Figure 1 reflects controlled model complexity and greater robustness, while still achieving substantive separation across the distribution of predicted propensity.

Overall, these results highlight the main strengths of the Archetype-Informed Logistic Regression: it outperforms naive fuzzy aggregation, offers clearer

behavioural interpretability than standard Logit, and provides a stable intermediate level of discrimination that remains competitive with more flexible machine-learning approaches while retaining full interpretability through the archetypal structure.

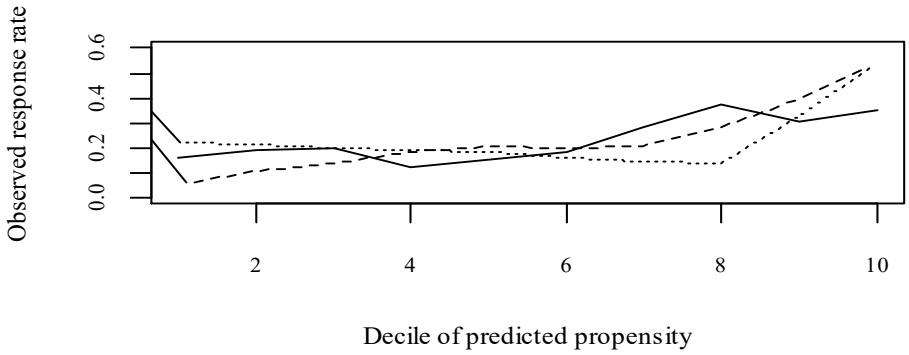

Figure 1: Observed response rates by decile of predicted propensity for Archetype-Informed Logistic Regression (solid line), Logistic Regression (dashed line), and Random Forest (dotted line). 2022 Istat Permanent Business Census.

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Artificial Intelligence and Innovation Spillovers: Evidence from Italian Provinces

Emma Bruno, Rosalia Castellano and Gennaro Punzo

Abstract This paper analyses innovation spillovers within the Regional Knowledge Production Function framework by introducing an AI-based spatial weight matrix that captures similarity in sectoral AI exposure. Innovation, proxied by patent intensity, is investigated for Italian provinces using a spatial Durbin panel model. The results support a competitive rather than cooperative interpretation of spatial interdependence among provinces with similar AI exposure, whereby higher innovative performance in one province is associated with lower patenting activity in structurally similar areas. In this context, R&D investments primarily reinforce local innovation advantages rather than generating positive spillovers across provinces similarly exposed to AI.

Key words: innovation, spillovers, spatial weights, artificial intelligence, Italy

1 Introduction

Innovation is widely recognised as a key driver of economic growth and territorial competitiveness [12]. Innovation processes are commonly analysed through the Regional Knowledge Production Function (RKPF), which relates innovative output to the availability of knowledge inputs, primarily research and development activities and human capital [7]. Within this framework, innovation results from cumulative processes that take place over time and reflect both local endowments and the broader environment in which regions operate [4]. Moreover, knowledge is characterised by

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limited appropriability and partial non-rivalry, which generates spillover effects across space and makes innovation activities inherently spatial, as knowledge created in one territory may influence the innovative performance of other areas through diffusion, imitation or competition [10]. Studies have traditionally focused on geographical proximity as the main channel for innovation spillovers [5]. More recent contributions have broadened this perspective by considering alternative proximity dimensions, showing that economic similarity, reflected in productive or occupational structures, can sustain spillover effects beyond geographical neighbourhoods [3,6]. Additional forms of proximity, including technological, social, and institutional linkages, have also been examined [2,13].

Building on this strand of research, this paper draws on the RKPF framework to assess innovation spillovers through a proximity matrix based on artificial intelligence (AI). Given the pervasive impact of AI in production processes and innovation activities, a spatial weight matrix grounded in sectoral AI exposure is constructed to assess whether similarities in AI exposure constitute a channel for innovation spillovers.

2 Materials and Methods

This study analyses innovation across 107 Italian provinces over the period 2010–2021. Innovation output is proxied by patent intensity, measured as the number of patent applications filed with the European Patent Office (EPO) per million inhabitants. Explanatory variables include research and development expenditure, measured as a percentage of gross domestic product (R&D), and human capital (HUC), proxied by the share of the population aged 24-39 with tertiary education. Moreover, the analysis includes a set of control variables: i) the relative change in provincial GDP, used as a proxy for economic growth; ii) the share of young people aged 15–29 who are not in employment, education, or training (NEET); iii) local institutional quality, measured by the Institutional Quality Index (IQI); and iv) entrepreneurial activity, proxied by the net balance between registered and terminated enterprises relative to the total number of firms in the commercial register (REG). Consistent with the research objectives, innovation determinants are estimated through a spatial Durbin panel model (SDPM), which allows accounting for global and flexible spillover effects of innovation [8]. In this framework, changes in a covariate within a spatial unit affect not only local innovation outcomes (direct effects) but also innovation performance in other units (spillover effects).

This study adopts a novel specification of the spatial weights matrix, alongside matrices based on geographical contiguity and economic and technological similarity [3] that captures similarity in AI exposure by sector of economic activity. Following Guarascio et al. [11], the industry-level measure of AI exposure (AIIE) developed by Felten et al. [9] is adapted to the Italian context to construct provincial indicators of AI exposure (AIPE) by sector of economic activity. Under the assumption that AI-relevant workplace tasks in U.S. occupations are comparable to those in European occupations [1], U.S. industries classified under NAICS are mapped to the

corresponding European NACE Rev. 2 classification. Next, using 2021 employment data, the AIPE by sector is computed by weighting the provincial employment share of each industry by its corresponding AIIE value. Formally, the AIPE for the i-th province and the k-th sector is calculated as $AIPE_{ik} = \frac{EMP_{ik}}{EMP_i} AIIE_k$, where EMP_{ik} denotes the number of employees in the k-th sector for the i-th province, EMP_i is the total number of employees in province i, and $AIIE_k$ is the industry-level indicator of AI exposure. To construct the spatial weight matrix, provincial proximity is defined in terms of similarity in AI exposure across sectors of economic activity. Similarity is measured using cosine similarity between provincial AIPE vectors, while differences in overall intensity of AI exposure are accounted for through a scale-adjustment factor. As a result, a weight of one is assigned if two provinces have both the same distribution of AI exposure across sectors and the same exposure intensity while differences along either dimension are penalised.

3 Main results and discussion

The estimation strategy was guided by a set of specification tests. The locally robust panel Lagrange Multiplier test showed significant spatial lag dependence. The Likelihood Ratio test favoured the SDPM over the panel spatial autoregressive (SAR) specification. According to the Pesaran test for cross-sectional dependence, the specification with time fixed effects best captures cross-sectional correlation and is therefore selected as the preferred model.

Table 1 shows the results of the SDPM with time fixed effects using the AI exposure-based spatial weight matrix[1]. R&D and HUC display positive and significant direct effects on patent intensity, in line with the RKPF framework. HUC has positive spillover effects, highlighting the contribution of skilled workforces from neighbouring provinces to local innovation through knowledge exchange and shared experience. By contrast, R&D generates negative spillover effects, pointing to competitive mechanisms across provinces, whereby R&D activities primarily strengthen local innovative capacity rather than spread benefits to structurally similar provinces.

Turning to the control variables, GDP positively influences local innovation, while its negative spillover effects suggest that economic growth in one province is associated with reduced patenting activity in other provinces characterised by similar sectoral AI exposure. The share of NEETs negatively affects local innovation performance, highlighting the importance of youth participation in the labour market and entrepreneurial culture for innovation capacity. IQI and REG show positive and statistically significant direct and spillover effects. This means that stronger institutions and more dynamic entrepreneurial environments foster knowledge creation and diffusion, thereby enhancing innovation propensity.

[1] For comparison, estimates based on geographical contiguity (W1), economic proximity (W2), and technological proximity (W3), constructed following Bruno et al. [3], are available upon request.

Finally, the significant and negative spatial autoregressive coefficient (ρ) indicates that higher innovative performance in a province is associated with lower patenting activity in provinces with similar AI exposure by sector. In this context, innovation propensity reflects competitive spatial interdependence rather than positive spillover effects. This result is consistent with the negative spillover effects associated with R&D expenditure, suggesting that R&D investments tend to reinforce local innovation advantages while limiting the diffusion of benefits across provinces that are similarly exposed to AI.

Table 1: Direct and Spillover Effects from the SDPM with time fixed effects

	Var.	*Direct effects*	*Spillover effects*
RKPF input	R&D	0.29***	-0.17***
	HUC	0.24***	0.51***
Control	GDP	1.62***	-1.34***
	NEET	-1.07***	-0.18
	IQI	0.25***	0.43*
	REG	0.23***	0.24***
	ρ	-0.17***	
	LogLik	-906.22	

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Artisanal enterprises and territories: sectoral dynamics and spatial patterns at the municipal level

Antonella Bianchino, Agata Maria Madia Carucci, Roberto Antonello Palumbo and Giovanni Vannella

Abstract The crisis of craftsmanship represents a significant phenomenon from an economic perspective, especially regarding territorial identity and social cohesion implications. This paper analyses, at the municipal territorial level, Italian craft sector evolution for the period 2014–2023 adopting a dual quantitative approach based on data from ISTAT's ASIA Business Register. The analysis is conducted by a spatial analysis using Local Indicators of Spatial Autocorrelation (LISA-Moran's I). The results highlight a widespread decline in the number of artisan enterprises and marked territorial heterogeneity: while temporal changes do not show significant spatial autocorrelation, the share of artisan enterprises in total enterprises displays relevant spatial patterns that differ across macro-sectors.

Key words: spatial autocorrelation, artisanal sector, ASIA, Moran's I

1 Introduction

Recent socio-economic literature has highlighted the commercial sector transformation, emphasizing processes such as commercial desertification and urban gentrification and their impacts on urban structure and territorial cohesion (see Cirelli, 2016).

Alongside these trends, the crisis of craftsmanship is emerging as a critical issue, particularly for more fragile territories, where artisanal activities contribute to local identity and social cohesion beyond their economic role.

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Against this background, this paper analyses, at the municipal territorial level, Italian artisanal sector evolution between 2014 and 2023, through applications of spatial methods based on local indicators of spatial autocorrelation (LISA - Moran's I) (Anselin, 1995) to investigate both temporal dynamics and territorial patterns.

2 Data and methodology

The analysis is based on Istat's ASIA Enterprises statistical register (EUROSTAT. 2010), referring to the years 2014 and 2023. The dataset includes a specific flag that allows the identification of artisanal enterprises, enabling a consistent selection of the artisanal segment within the productive system.

The definition of an artisanal enterprise refers to the Italian regulatory framework established by the Framework Law on Craftsmanship (Law n. 443/1985).

According to this legislation, artisanal enterprises are identified on the basis of employment size thresholds, which vary depending on the type of production process (serial or non-serial) and the sector of activity.

Spatial autocorrelation is analyzed using both global and local Moran's indicators (LISA - Moran's I) (Anselin, 1993). In a first step, these indicators are applied to the percentage variation in the number of artisanal enterprises at the municipal level, in order to assess the presence of spatial dependence in the temporal dynamics of the phenomenon. Subsequently, the analysis is extended to the incidence of artisanal enterprises relative to total firms by macrosector, with the aim of identifying local spatial patterns and homogeneous territorial clusters.

The analysis is conducted using a spatial weights matrix based on territorial contiguity between municipalities.

3 Results

In 2023, over one million artisanal businesses will be operating in Italy, representing approximately 21% of all active businesses and 2.5 million employed workers. Compared to 2014, the number of artisanal businesses decreased by approximately 100,000, resulting in a total loss of 234,000 jobs. The contraction of artisanal enterprises is not homogeneous across regions or sectors. From a geographical perspective, the most pronounced decline is observed in the North-East (-10.9%), which also records a reduction of approximately 100,000 workers (-12.8%).

By contrast, the South of Italy shows a greater resilience of the sector (-8.2%), particularly in employment terms, with a decrease in the number of workers of 3.6%.

From a sectoral perspective, "Other service activities," "Construction," and "Manufacturing" display the highest relative incidence of artisanal enterprises.

However, despite a general decline in the number of artisanal firms across most economic activities, the "Information and communication services" and "Business support services" sectors register the most marked increase in the number of artisanal

enterprises over the period considered, pointing to a gradual shift in the sectoral composition of craftsmanship. The municipal level percentage changes in the number of artisanal enterprises across the four macro-sectors (Fig. 1) indicate a widespread contraction between 2014 and 2023, although with differing intensities across sectors.

The dynamics appear spatially fragmented and lack continuous territorial patterns, in line with the absence of a spatial autocorrelation structure in the variations, as confirmed by the LISA - Moran's I indicators. From a sectoral perspective, declines are more pronounced in manufacturing and in the trade, transport, and accommodation sector, while construction exhibits greater territorial heterogeneity and a higher share of municipalities showing relative stability or growth.

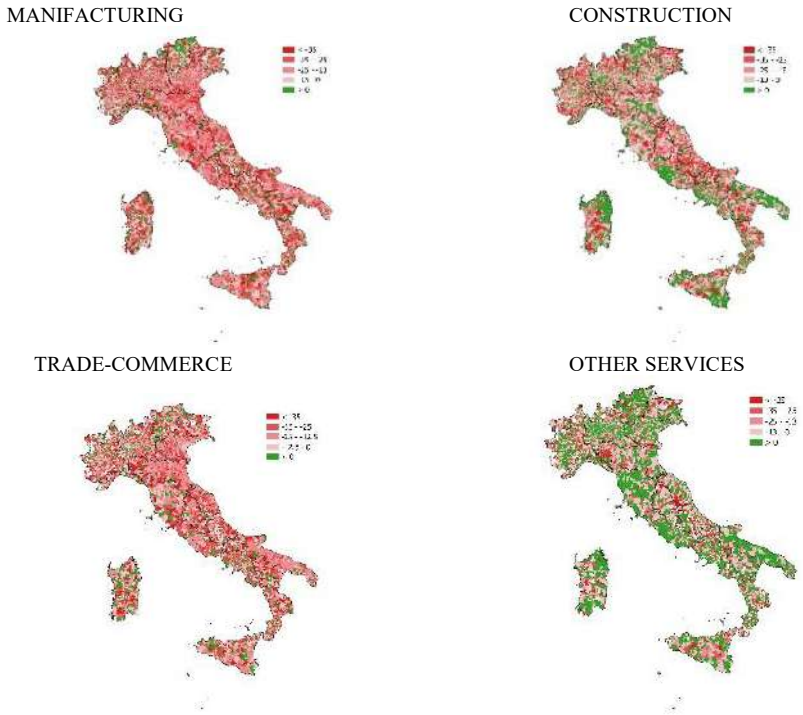

Figure 1: Percentage Change in the Number of Artisan Firms by Macro-Sector (2014–2023)

While the temporal dynamics of the number of artisanal enterprises do not exhibit a spatial dependence structure, a different picture emerges when the focus shifts from temporal change to the structural distribution of artisanal enterprises.

Accordingly, the following section examines the spatial autocorrelation of the incidence of artisanal enterprises relative to total firms by macro-sector (Fig. 2).

The spatial autocorrelation analysis (GeoDa, 2017) of the incidence of artisanal enterprises relative to total firms reveals marked heterogeneity across macro-sectors. Manufacturing exhibits more spatially concentrated and selective clusters, while the construction sector displays a more articulated spatial configuration, with the coexistence of areas characterized by high and low artisanal incidence. In the trade, transport, and accommodation sector, more extensive clusters of low incidences emerge, indicating a weaker artisanal specialization, whereas other service activities are characterized by a more fragmented and less polarized spatial distribution.

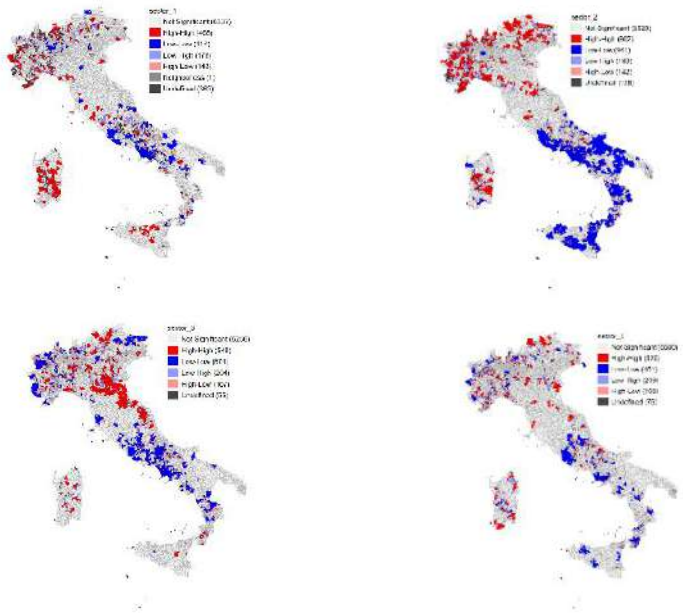

Figure 2: Incidence of artisanal enterprises by Macro-Sector. LISA map resulting from local Moran index. Year 2023

4 Conclusions

This paper analyzes the evolution of craftsmanship in Italy between 2014 and 2023, highlighting a widespread decline in the number of enterprises alongside marked territorial and sectoral differences. The spatial analysis shows that temporal variations do not exhibit a spatial autocorrelation structure, whereas the incidence of artisanal enterprises relative to total firms reveals significant spatial patterns that differ across macro-sectors. This suggests that the crisis of craftsmanship does not unfold as a uniform process, but rather as a phenomenon closely linked to local productive specialization. Overall, the results confirm the role of craftsmanship as a structural component of territorial systems and point to the need for policy interventions that are sensitive to the sectoral and territorial specificities identified.

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Assessing Urban Social Investment Across Milan's Municipalities Through Composite Index

Jurgena Myftiu

Abstract The paper analyses spatial disparities in social investment across the province of Milan by constructing a composite indicator based on the stock–flow–buffer framework. Using municipal data for 133 municipalities over 2018–2020, it identifies a persistent north–south divide, with stronger performance in northern and western areas and weaker outcomes in the southern periphery. Stock and buffer components appear relatively stable, while the flow dimension is more volatile, reflecting uneven local labour market capacity. Milan displays a distinctive pattern: strong education and welfare resources alongside fragmented labour dynamics. The results point to embedded inequalities and stress the role of multilevel governance and fiscal coordination in strengthening social investment in lagging areas.

Key words: Adjusted Mazziotta–Pareto Index, Territorial Policy, Subnational Analysis.

1 Introduction

Over the past two decades, social investment (SI) has emerged as a key framework in the transformation of European welfare states [4, 7]. By integrating education, labour market participation, and social protection, the SI approach aims to promote inclusive growth while strengthening the sustainability of welfare systems [1, 2].

While the SI debate has been largely developed at the national level, increasing attention has been devoted to its territorial dimension. Local and regional governments play a growing role in the provision of education, welfare services, and active labour market policies, making subnational and metropolitan contexts crucial for understanding how SI strategies are implemented in practice [5, 8, 9].

Within this perspective, the SI paradigm conceptualises welfare policies as an integrated system combining human capital formation, labour market integration,

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and social protection. This multidimensional structure is commonly captured through the *stock–flow–buffer* framework, where *stock* policies support education and skills accumulation, *flow* policies facilitate labour market transitions, and *buffer* policies provide income support and social services to mitigate social risks [4]. Assessing SI therefore requires analytical tools capable of accounting for imbalances across these interrelated dimensions, rather than focusing on single policy domains.

Despite the rising policy relevance of local welfare, empirical evidence on SI performance at the municipal level remains limited. Existing studies often rely on single indicators or sector specific measures, overlooking the multidimensional nature of SI and hindering systematic territorial comparisons [3, 6].

This paper addresses this gap by proposing a composite indicator approach to assess SI performance at the municipal level within the province of Milan. Using municipal data for 133 municipalities over the period 2018–2020, the study provides new evidence on the spatial distribution and persistence of SI capacities within a major Italian metropolitan area, contributing to the territorialisation of the SI paradigm.

2 Data and methodology

The empirical analysis is based on municipal level data drawn from *A Misura di Comune*, a multi-source statistical framework developed by the Italian National Institute of Statistics (ISTAT). The dataset covers 133 municipalities in the province of Milan over the period 2018–2020, the most recent years for which a consistent set of indicators is available.

SI performance is operationalised through a set of 21 indicators organised according to the *stock–flow–buffer* framework [4]. The *stock* dimension captures human capital accumulation through indicators related to educational attainment and childcare provision. The *flow* dimension reflects labour market integration and employment stability, distinguishing between full time and part time work as well as permanent and fixed-term contracts. The *buffer* dimension measures municipal social protection capacity through per capita expenditure on social services targeting families, older people, disability, poverty, and other vulnerable groups.

To aggregate individual indicators into synthetic measures, the analysis adopts the Adjusted Mazziotta–Pareto Index (AMPI), a non-compensatory composite indicator designed for multidimensional socio-economic phenomena [6]. Composite indices are computed separately for each pillar and then combined into an overall SI Index, allowing comparisons across municipalities and over time.

3 Results

The composite index reveals marked spatial disparities in SI performance across municipalities in the province of Milan. Over the period 2018–2020, a stable territorial pattern emerges, characterised by a pronounced north–south divide. Higher levels of SI are consistently observed in the northern and western municipalities, while lower scores prevail in the southern and southwestern

periphery. This spatial configuration mirrors broader socio-economic differences in income levels, labour market stability, and fiscal capacity within the metropolitan area.

Figure 1: Spatial distribution of the SI Index across municipalities in the province of Milan, 2018–2020

Figure 1 illustrates the geographical distribution of the SI Index for the years 2018, 2019, and 2020. The maps highlight the persistence of spatial inequalities over time, with limited changes in the relative position of municipalities. High performing areas remain clustered in the northern and western parts of the province, while municipalities in the southern periphery consistently display lower levels of SI.

Disaggregating the results by functional dimensions provides additional insights into the drivers of these patterns. The *stock* dimension displays a relatively stable spatial distribution, indicating persistent differences in human capital accumulation linked to education and childcare provision. By contrast, the *flow* dimension shows greater variability across both space and time, reflecting the uneven capacity of local labour markets to sustain stable and inclusive employment.

When the three pillars are combined into the overall SI Index, the results confirm the persistence of territorial inequalities throughout the period analysed. Municipalities with stronger initial endowments in human capital, employment stability, and fiscal resources consistently achieve higher scores, while structurally weaker municipalities remain concentrated at the lower end of the distribution. The municipality of Milan exhibits a distinctive profile, combining strong performance in the *stock* and *buffer* dimensions with comparatively weaker outcomes in the *flow* dimension, reflecting a labour market that is dynamic yet fragmented.

4 Discussion and conclusions

The analysis highlights a persistent and spatially polarised pattern of SI within the province of Milan. The stability of municipal positions over the period 2018–2020 suggests that SI capacity is strongly conditioned by structural and institutional factors rather than by short term policy adjustments. Municipalities characterised by higher human capital endowments, more stable labour markets, and stronger fiscal capacity consistently outperform peripheral areas, reinforcing existing territorial divides.

These findings support a territorial interpretation of the SI paradigm, according to which welfare outcomes depend not only on policy orientation but also on the governance capacity and resource endowment of local contexts [2, 4]. Metropolitan

areas thus emerge as both engines of welfare innovation and sites of cumulative disadvantage, where SI outcomes are unevenly distributed across space.

The case of Milan exemplifies this duality. While the city performs strongly in terms of human capital and social protection, its weaker performance in the labour market dimension points to persistent fragmentation and employment instability. This confirms that strong welfare infrastructures do not automatically translate into inclusive labour market outcomes in large metropolitan economies.

In conclusion, this study contributes to the territorialisation of the SI paradigm by providing a synthetic and comparable assessment of municipal performance within a major metropolitan area. The evidence highlights the need for territorially sensitive policy frameworks and metropolitan level coordination capable of addressing structurally embedded inequalities in local social investment capacity.

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Automated Business Data Collection in Official Statistics: An Experimental Study

Diego Distefano, Paola Bosso, Giovanni Gualberto Di Paolo and Pasquale Papa

Abstract The study assesses, within a multi-source approach to official business statistics, the potentialities of a new data source related to Industry 5.0. The experimental analysis focuses on the single variable 'industrial production in volume'. It is structured in two phases: the first examines, through structured interviews, the potential of data generated by advanced ERP systems for statistical purposes; the second involves businesses participating in the monthly industrial production survey to evaluate compliance with EU standards and the level of data acceptance. Using ERP data for automated M2M transmission can reduce costs and respondent burden while improving data quality and timeliness.

Key words: Industry 5.0, official statistics, multi-source approach, ERP systems, automated data collection, burden reduction

1 Background and objectives

The development of Artificial Intelligence (AI) models and new technologies applied to industrial processes (Industry 5.0) offer new opportunities for official business surveys [4]. This paper presents an experimental study aimed at improving data integration and statistical production through a multi-source approach that exploits AI and emerging digital technologies. Automating business data collection processes can also reduce costs and respondent burden while improving timeliness

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and accuracy. The study is organised into two main phases: interviews with advanced ERP system developers, to assess the data structures embedded in the platforms, their compliance with statistical requirements, and the potential use of AI for data retrieval, processing, and automated transmission. Interviews with enterprises using advanced ERP systems, to evaluate the feasibility of producing statistics aligned with European standards by applying AI and automated data collection techniques, while also assessing usability and enterprise acceptance. Preliminary assessments focus on the potential gains in terms of time and costs incurred by respondents participating in short-term surveys. The data are drawn from Istat's direct survey management systems and are based on average completion times for short-term survey questionnaires and estimated average labour costs expressed in person-hours. The digital transformation driven by Industry 4.0 and Industry 5.0 has greatly increased the availability, level of detail, and timeliness of real-time data generated by enterprises. At the same time, organisations are increasingly adopting a comprehensive view of their operations, conceptualising the value chain as an integrated and interconnected system rather than a collection of standalone activities. As supply chains become increasingly complex and customer-focused, data is widely acknowledged as a strategic resource. Emerging technologies are reshaping supply chains into adaptive, intelligent networks. Together, these developments signal a fundamental transition toward integrated, data-driven systems that enhance both business performance and the production of modern, responsive statistical outputs.

2 Data collection based on large scale AI and M2M applications

According to the approach described, the experimental trial involves the implementation of a set of operational phases, outlined below:

2.1 Experimental domain and ERP providers assessment

Selection of a reference variable for the trial: the variable selected for the initial experimentation involving the new approach is the industrial production expressed in volume [1]. This choice is driven by practical and methodological reasons. Currently, this data is only collected through direct surveys and is not available from administrative sources. Meanwhile, Industry 5.0 platforms have strong capabilities to capture this type of data, making it an ideal subject for testing new statistical processes. At present, the selected variable is obtained exclusively through direct surveys: Monthly Survey on Industrial Production (IPI) And Annual Survey on Industrial Production (Prodcom). The activity focuses on engaging key ERP platform providers to assess the operational feasibility of the project and the potential of new data sources. In this context, advanced ERP systems integrated with Manufacturing Execution System (MES) components appear to be the most suitable option for the purposes of the study. To collect structured feedback, a dedicated interview was developed. It explores the following topics: User Profile and Market Context, Industrial Process Digitalisation, AI-Based Services and

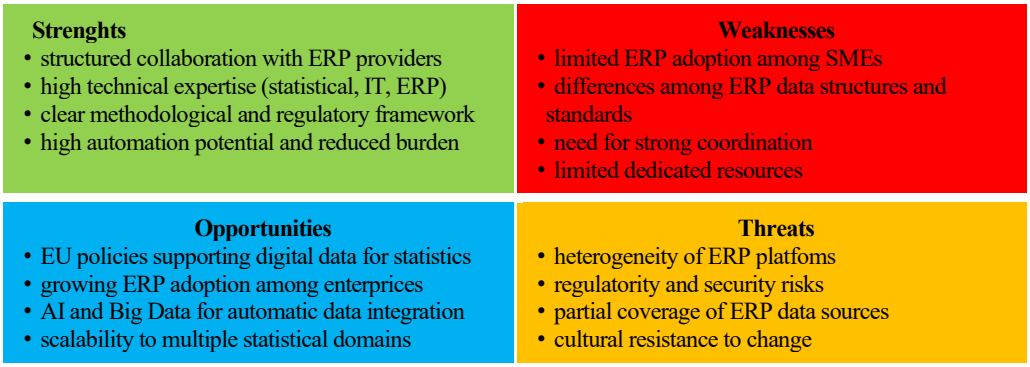
Applications, Process Automation and Optimisation, Data Management and Reporting, Automated Systems for Measuring Production Volumes. AI integration in modern ERP systems is a key differentiator, with applications like sales forecasting, predictive inventory, and document classification.

2.2 Businesses assessment and following phases

A specific phase of the project is dedicated to companies involved in the surveys, with the primary objective of assessing the acceptability of the new approach. Unlike conventional web surveys, the proposed method involves a more intrusive form of data collection [3]. Therefore, it is crucial to evaluate businesses' willingness to engage with the project and to identify any concerns or barriers that might affect their participation. In-depth interviews are used to explore two complementary aspects: on the one hand, the current processes already in place for collecting and transmitting production data in volume; on the other, the level of trust and acceptance of automated AI models and M2M data transmission compared with traditional web-based surveys. In the following, the main focus points: Structural Information, Internal Data Sources & Processes, AI Techniques, Attitudes toward a dedicated Data Transmission Module.

3 Early outcomes and discussion

Preliminary outcomes drawn from Istat's direct survey management systems indicate substantial potential benefits in terms of time savings and reduced manual effort for enterprises. For short-term surveys, reporting time could decrease by approximately 68% for enterprises with more than 20 employees and by 86% for those with over 250 employees. Across the entire population of enterprises with 20 employees or more, this corresponds to an estimated annual saving of about 165,000 working hours. Large enterprises would save on average 17 hours per year, equivalent to a total of approximately €4,943,000. In order to identify the main strengths, weaknesses, opportunities, and threats associated with this innovative approach the team involved in the experimental study decided to carry out a SWOT analysis (Figure 1). A sustainable implementation will require a comprehensive governance strategy focused on interoperability, transparency, and cooperation between statistical institutions, ERP providers, and the business community.



4 Conclusions

This study contributes to the ongoing debate on the transformation of official statistics by proposing and preliminarily testing a structured framework for the implementation of a generalised machine-to-machine (M2M) data reporting model based on specialised ERP modules designed for Industry 5.0 environments. The proposed approach situates automated data transmission within the broader transition from survey-centric systems toward integrated multi-source statistical systems. The preliminary findings highlight that automated M2M reporting has the potential to generate substantial gains in process efficiency, timeliness, and data quality, while significantly reducing respondent burden for enterprises involved in short-term surveys. Beyond operational improvements, the model represents a structural innovation in the relationship between National Statistical Institutes (NSIs) and data providers, shifting from episodic survey interactions to embedded, system-level data integration. In this respect, the study provides a strategic evaluation model that can support NSIs in assessing scalability, interoperability, and long-term sustainability of ERP-based reporting infrastructures. At the current stage, the empirical evidence confirms the existence of measurable potential benefits, although a precise quantification of efficiency gains and burden reduction remains subject to further experimentation. Future research will extend the analysis through structured impact measurement, including cost–benefit modelling and qualitative evidence derived from semi-structured interviews with enterprises and ERP providers. Overall, the results suggest that ERP-enabled M2M reporting may represent a pillar of next-generation statistical production systems, provided that technical innovation is accompanied by institutional coordination and a carefully designed governance architecture.

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Bubble and Crash Information in Markov-Switching GARCH Models: Evidence from Ethereum Volatility Forecasting

Andrea Montanino and Giovanni De Luca

Abstract In cryptocurrency markets, where extreme price events are pervasive, explicitly modelling bubbles and crashes is crucial to obtain accurate volatility forecasts. This study extends the Bubble–Crash filter to a Markov-Switching GARCH (MSGARCH) framework for Ethereum, combining PSY-based real-time bubble and crash dating with regime-switching volatility dynamics. Bubble and crash phases are incorporated into the conditional mean through dummy variables, yielding two specifications: an idiosyncratic model for Ethereum (BC-MSGARCH$^{\mathrm{OWN}}$) and a contagion-enhanced variant that also accounts for Bitcoin bubble phases (BC-MSGARCH$^{\mathrm{BTC}}$). One-step-ahead volatility forecasts are evaluated against a standard MSGARCH benchmark using Diebold–Mariano and Clark–West tests. The results show that explicitly modelling bubble and crash regimes—especially when incorporating Bitcoin signals—significantly improves volatility forecasting accuracy.

Key words: cryptocurrency, bubbles, crashes, MSGARCH, volatility.

1 Introduction

Since the Global Financial Crisis, econometricians have intensified the development of robust econometric tools to monitor and forecast extreme price episodes across asset classes. A major step forward came with recursive right-tailed unit-root testing and real-time monitoring frameworks [17, 18], together with complemen-

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tary contributions [16, 9]. Forecasting approaches include noncausal or stochastic specifications [10, 7, 11]. These tools are particularly relevant for cryptocurrency markets, where bubbles and crashes have been repeatedly documented [13, 15], and where volatility dynamics often display regime-switching behavior [1, 2, 4]. Motivated by recent attempts to connect exuberance/crash dating with volatility modeling [12]—and building on the MSGARCH framework widely used in this literature [8]—this study extends the Bubble–Crash (BC) filter [12] from a GARCH setting to MSGARCH. Focusing on Ethereum, we consider an idiosyncratic specification (BC–MSGARCH$^{\mathrm{OWN}}$) and a contagion-enhanced variant that also incorporates Bitcoin bubbles and crashes (BC–MSGARCH$^{\mathrm{BTC}}$), to compare one-step-ahead volatility forecasts accuracy against a standard MSGARCH using Diebold–Mariano [6] and Clark–West tests [5].

2 Methodology

First, the detection phase is performed on the logarithmic price series of Bitcoin and Ethereum, comprising 2,008 daily observations starting on January 1, 2019. The log-price series is split into an in-sample and an out-of-sample segment using a fixed cutoff date set at December 31, 2023. The PSY test [17] requires defining the minimum window size, set to 95 daily observations, the control period, fixed at 90 days, and the lag order l, equal to 0. During the out-of-sample period, the PSY test is applied sequentially on a day-by-day basis, adopting, to ensure consistency, the same set up of the in-sample part, by fixing the endpoint of the regression window at each new observation and searching backward over all admissible starting points. Critical values are computed via a bootstrap procedure using a 5% significance level and 500 Monte Carlo replications. After accounting for the minimum window size, the return series consists of 1913 daily observations.

The information on bubble and crash phases is incorporated into the conditional mean of returns through a Bubble–Crash specification, in which discrete indicator variables capture the occurrence of exuberant and collapsing price episodes. Specifically, the return process is modeled as

$$r_t = \mu + \theta_1^{\mathrm{OWN}} B_t^{\mathrm{OWN}} + \theta_2^{\mathrm{OWN}} C_t^{\mathrm{OWN}} + \varepsilon_t,$$

where B_t^{OWN} and C_t^{OWN} are dummy variables identifying, respectively, bubble and crash phases in the Ethereum market, as detected in real time by the PSY procedure. To account for potential contagion effects, the mean equation is augmented by including also the corresponding Bitcoin bubble and crash indicators, i.e. B_t^{BTC} and C_t^{BTC}, with coefficients, respectively, θ_1^{BTC} and θ_2^{BTC}.

Secondly, volatility is modeled using a two-regime Markov-switching framework, with first-regime volatility based on the GARCH(1,1) model [3] and second-regime volatility modeled by an EGARCH(1,1) model [14]. The innovations of both regimes are modeled by a normal distribution. Model parameters are estimated by

Maximum Likelihood, and one-step-ahead volatility forecasts are generated using a rolling window whose length coincides with the training sample (1732 observations). Accordingly, the out-of-sample period spans from January 1, 2024, to June 29, 2024, and the forecasting exercise delivers volatility predictions for the first six months of 2024.

3 Results and conclusions

Table 1 reports model comparisons related to Ethereum. According to all in-sample fit criteria (AIC, and BIC), the BC–MSGARCH$^{\text{BTC}}$ shows the best fit.

Table 1 Estimation results for Ethereum MSGARCH models. DM and CW p-values refer to comparisons vs. MSGARCH. Statistical significance: *** 1%, ** 5%, * 10%.

Parameter / Statistic	**MSGARCH**	**BC–MSGARCH$^{\text{OWN}}$**	**BC–MSGARCH$^{\text{BTC}}$**
Mean equation			
μ	–	0.131	0.048
θ_1^{OWN}	–	3.825***	3.020***
θ_2^{OWN}	–	-7.976***	-7.893***
θ_1^{BTC}	–	–	2.664***
Variance equation			
$\omega_{0,1}$	0.000	0.000	0.000
$\alpha_{1,1}$	0.038***	0.037***	0.037***
$\beta_{1,1}$	0.913***	0.917***	0.918***
$\omega_{0,2}$	0.567***	0.547***	0.605***
$\alpha_{1,2}$	0.503***	0.475***	0.441***
$\alpha_{2,2}$	-0.168***	-0.185***	-0.265***
$\beta_{1,2}$	0.896***	0.896***	0.875***
$P_{1,1}$	0.702***	0.703***	0.697***
$P_{2,1}$	0.711***	0.695***	0.698***
AIC	9577.649	9561.055	9538.673
BIC	9626.762	9610.169	9587.786
Ljung–Box (LB) p-values			
LB(ε_t,1)	0.861	0.920	0.964
LB(ε_t,2)	0.207	0.346	0.282
LB(ε_t^2,1)	0.507	0.521	0.352
LB(ε_t^2,2)	0.706	0.659	0.550
p-value (vs. MSGARCH)			
DM (MAE)	–	0.010	0.000
DM (MSE)	–	0.011	0.000
CW	–	0.001	0.000

The coefficients associated with extreme price events are coherent in sign and highly statistically significant. The significance of the Bitcoin bubble indicator coefficient at the 1% level provides clear evidence of cross-market spillovers from Bitcoin to Ethereum. From a forecasting perspective, the Diebold–Mariano and Clark–West tests strongly reject the null of equal predictive accuracy in favor of the BC–MSGARCH specifications. The gains are statistically significant at the 1% level, with the largest improvements observed for the BC–MSGARCH$^{\text{BTC}}$ model.

The results confirm that explicitly accounting for bubble and crash phases improves model specification, significantly improving one-step-ahead volatility forecasts of returns.

Future research may extend this approach to multi-step forecasting horizons and the prediction and backtesting of Value-at-Risk and Expected Shortfall.

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Business Acumen and Firm Performance: Modeling the Impact of Marketing Decisions through a Dynamic Framework

Raffaele Angelone, Giampiero Data and Paolo Mariani

Abstract This paper proposes a critical review of firm performance measurement by introducing the concept of Business Acumen as the causal link between operational decisions and financial outcomes. Moving beyond the static view of traditional KPIs, this study demonstrates that performance, as reflected in the Profit & Loss (P&L) statement, is a non-linear dependent variable influenced by the product lifecycle stage. The exercise focuses on the construction of a marketing plan, utilizing activation matrices to optimize the investment mix within the department and simulate "what-if" scenarios.

Key words business acumen, product life-cycle, profit &loss, decision making

1 Introduction

In both managerial and statistical literature, firm performance is often treated as an ex-post accounting figure. However, for management, the challenge lies in the ability to predict how operational choices made today will impact future results. Business Acumen represents this competence: the ability to understand and model the link between decision-making levers and their financial reflections in the Profit & Loss (P&L) statement.
The P&L is not merely a reporting document but the final "scorecard" of strategic effectiveness. Although performance is the outcome of synergistic actions across all

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corporate components, this study adopts marketing decisions as the primary driver to illustrate a performance simulation model that is truly decision-oriented. A common limitation in performance measurement models is the assumption of linearity and stationarity. On the contrary, the relationship between investment and results strictly depends on the Product Lifecycle (PLC) stage. For example, in the launch phase of a product the primary objective is building adoption (Trial Rate). In this phase, a P&L with negative margins may represent excellent performance if accompanied by high market activation rates. Models must prioritize latent variables and qualitative proxies (awareness, sentiment) here. On the opposite, in the maturity phase, objectives shift toward marginal efficiency and cash generation. Performance is measured through margin stability and cost optimization.
Therefore, the interpretation of results must be "phase-aware": the same KPI (e.g., ROI) carries different meanings and weights depending on where the product stands in its lifecycle.

2 Data and Methodology

To fuel the decision loop, the framework requires the integration of heterogeneous data streams. The study specifically analyzed how different strategic choices and marketing plans impact key P&L indicators across the various stages of the product lifecycle. The integration process involves:

a) Decision Data: Marketing investment logs, resource allocation, and plan costs;

b) In market results: Sales data (sell-in/sell-out), accounting data, and market share**;**

c) Behavioral Proxies: Qualitative signals (e.g., brand loyalty or persistence of use) that act as leading indicators of future financial performance.

By mapping these datasets, the study evaluated the impact of specific marketing mixes not only on immediate profitability but also on long-term financial sustainability. This approach allows for a granular understanding of how resource allocation in the early stages (e.g., Launch) creates a "value carry-over" effect that ensures the firm's financial health and stability over time.
The core of the implementation consists of building a marketing plan supported by "what-if" scenario models. In this experimental phase, the activation matrix was specifically applied to the activities and sub-components of the marketing department to test its effectiveness in resource allocation.

3 Remarks and conclusions

The application of the activation matrix was specifically aimed at marketing mix optimization. Through the multiplier matrix, it was possible to simulate various investment configurations (e.g., varying combinations of digital channels, events, and field force) to identify the mix capable of maximizing financial performance in the P&L.

This approach moves beyond simple expense planning: the model identifies how the input of a specific marketing activity generates value through other sub-functions within the department. Mix optimization is therefore not intended as mere cost-cutting, but as identifying the combination of levers that minimizes internal friction and maximizes impact on EBIT, based on the identified technical transformation coefficients between activities. While the current exercise focused on the marketing perimeter, its methodological value lies in its potential extension. The applied logic is natively structured to overcome departmental "silos." In a subsequent phase, including other departments (Supply Chain, HR, Finance) in the technical coefficients' matrix would allow for mapping the systemic interdependencies of the entire firm. In this expanded scenario, the model would be able to show how a marketing decision impacts not only the departmental budget but also triggers resources in other functions (e.g., logistics), ensuring total strategic coherence and truly integrated firm-level performance measurement.

The study demonstrates that firm performance should not only be measured but modeled as a function of decisions and temporal context. Adopting activation matrices for marketing mix optimization represents a first step toward management based on quantitative Business Acumen.

In conclusion, performance measurement becomes meaningful only when embedded in a decision loop capable of simulating the future and the interaction between different components, rather than being limited to a static reporting of the past.

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Core Determinants of the Dynamics of a Currency Board: The Fragility Behind the Peg

Eleonora Cavallaro and Bernardo Maggi

Abstract In this research, we study a 2×2 dynamical model for a currency board, where the growth of domestic liquidity is strictly governed by the dynamics of foreign reserves, i.e., the balance of payments. We refer to Argentina's experience and employ a nonlinear continuous-time model to obtain more precise coefficients in terms of both efficiency of estimations and speed of convergence. In our dynamic setting, expectations of a blooming economic growth foster debt-generating capital inflows; this, in turn, determines the build-up of debt, which curbs agents' state of confidence.

Key words: Macrodynamics, Financial Fragility, Currency-board Arrangement, Continuous-time Econometrics, Long-Run Equilibrium, Stability Analysis.

1 Introduction[1]

The issue of the sustainability of a fixed peg has been addressed back, in the past, first by [3] who started considering with perfect foresight, the implications of the exhaustion of the stocks of reserves, with perfect foresight, and then by [4] who considered the possibility of self-fulfilling expectations as the driver of the crisis, with rational (i.e., according to the conditional mean) expectations. Later, [5] con-

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[1] We are grateful to the University of Rome La Sapienza for funds provided to support this research, grant n. RD124190DA1146AA. We especially wish to thank Clifford Wymer for helpful comments and suggestions.

sidered the possibility of two multiple equilibria of output, i.e., a good equilibrium and a bad equilibrium, for a country that minimizes a loss function, where the social cost of a low output (in case of the the bad equilibrium) is traded-off against the cost of exiting arrangements to regain the monetary and fiscal policies autonomy. Clearly, an anti-cyclical monetary policy might contribute to boost the economy, raising employment and output. However, a hard peg can impede this policy response, and then the main question becomes if the cost of exiting the agreements is lower than the cost of bearing the low levels of output and employment.

Using a continuous-time model, we study the dynamics of the currency board based on Argentina's experience to understand if and how a fixed peg arrangement invoked to induce stability and promote growth can produce the opposite outcome, i.e. accentuate structural imbalances and drive the economy to a condition stagnation. While initially curbed hyper-inflation, it became unsustainable as trade flows remained concentrated within Mercosur economies, which were depreciating their currencies. The pesos'over-evaluation (due to its 1:1 link to the dollar) widened current account deficits and led to a severe balance-of-payments crisis.

To show this interplay, we focus on the dynamic interaction between domestic liquidity, which matches the stock of reserves, as required by the currency board arrangement, and the state of confidence regarding the economy's growth prospects.

We build on [2] and [1] where the interaction of the two key variables is part of a larger model that includes the dynamics of output and the interest rate, among others. Moreover, [2] is enriched with a calibrated anti-cyclical monetary policy, and [1] with a direct fiscal policy, to control the instability of the model.

In Section 2, we describe the dynamic interplay between debt and the state of confidence. In Section 3, we present data and estimation results. In Section 4, we study the nature of the steady-state equilibria and the out-of-steady-state dynamics and draw the conclusions

2 A simple 2×2 Nonlinear Dynamical System

We consider a 2×2 model for two simultaneously endogenous variables, respectively, the stock of domestic liquidity l, as resulting from the debt-generating capital inflows, and the state of confidence ρ.

The system is described in the block (3), obtained from blocks (1) and (2). Specifically, in $\dot{l}$, we state that the change in the stock of foreign debt, i.e., the capital inflows, is a function of the difference between investors' desired capital l^f and its outstanding level l. We can think of l^f as representing foreign investors demand for bonds issued by the government or domestic firms. The demand l^f depends nonlinearly on the country's growth prospects, ρ. In $\dot{\rho}$ we state that the change in ρ obeys an adjustment scheme, i.e., increasing when the expected state of confidence ρ^f exceeds its actual level ρ. In (2) we state that the expected state of confidence ρ^f has an autonomous component and is negatively influenced by the outstanding stock of debt, l.

There are no exogenous variables, thereby excluding any fiscal and/or monetary intervention, as dictated by the currency regime. The non-linearity we consider captures the negative counter-effect of *euphoria* on capital inflows when the state of confidence ρ is beyond a threshold.

$$\begin{cases} \dot{l} = k_1(l^f - l) \\ l^f = a_0 + a_1\rho + a_2\rho^2 \end{cases} \tag{1}$$

$$\begin{cases} \dot{\rho} = k_2(\rho^f - \rho) \\ \rho^f = b_0 + b_1 l \end{cases} \tag{2}$$

$$\begin{cases} dl = (k_1a_0 + k_1a_1\rho + k_1a_2\rho^2 - k_1l)dt + dW_1(t) \\ d\rho = (k_2b_0 + k_2b_1l - k_2\rho)dt + dW_2(t). \end{cases} \tag{3}$$

The error terms, $W_i(t)$ are Gaussian processes, as usual with stochastic differential equations, with $dW_i \sim \text{i.i.d.}(0, \sigma^2_{W_i}),\ i = 1,\ 2,\ E[W_i(t)] = 0$ and $E[W_i(t_2) - W_i(t_1)][W_i(t_4) - W_i(t_3)]' = \mathbf{0}$, $E[W_i(t+dt) - W_i(t)][W_i(t+dt) - W_i(t)]' = \boldsymbol{\Omega}(dt)$.

Since the system aims at studying the balanced growth path, where domestic liquidity grows at the same constant rate of capital, in the above equations $l = L/K$, with L the stock of outstanding loans and K the stock of capital.

3 Dataset and Estimation

We use quarterly data for Argentina based on the EIU country dataset for the currency board period, specifically, 1991-2001. For the state of confidence, we consider the difference between the GDP moving average and potential output, out of potential output, as representing the economy's growing prospect.

We estimate the continuous-time dynamic models according to the *exact discrete analogue* method.[2]

4 Qualitative Analysis and Conclusions

The model has two equilibria. One equilibrium is stable, $[l_1^*,\ \rho_1^*]$=[0.0410, 0.0498], with two coincident complex and conjugates eigenvalues, $\lambda_{1,1}$= -0.250 + 0.160i and $\lambda_{1,2}$= -0.250 - 0.160i. The other equilibrium is unstable, $[l_2^*,\ \rho_2^*]$=[0.0028, 0.196], with $\lambda_{2,1}$= -0.638 and $\lambda_{2,2}$= 0.138. As we can see from Figure 1 the unstable equilibrium has a saddle path, while the stable equilibrium is a focal point, and is an attractor with spirals for its region. The unstable equilibrium is a saddle point with a

[2] The nonlinear estimation and sensitivity analysis of the models have been performed, respectively, by means of Escona (2005) and Contines (2005) C. Wymer's programs, and Matlab(2022). The estimation method is that of FIML.

Table 1: Non-linear-system coefficients-estimation

Parameter	Point FIML Estimates	Asymptotic Standard Error	t-values
a_0	0.0181***	0.0049	3.69
a_1	0.6441***	0.2020	3.19
a_2	-3.6853**	1.9200	1.92
b_0	0.2064***	0.0775	2.66
b_1	-3.8185**	1.9263	1.98
k_1	0.3902***	0.1099	3.55
k_2	0.1100***	0.0357	3.08

straight line that allows convergence. In Figure 1 we can see that from the actual initial conditions in 1991, the system structurally ends in the stable equilibrium. However, the trajectory shows that without accounting for exogenous effects, the system crosses a region not allowed with null and impossible negative liquidity due to the capital flight, which would mean a situation of extreme poverty without money.

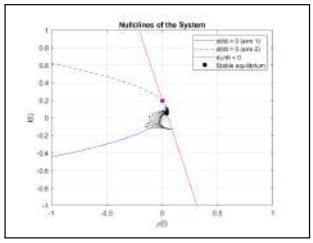

Fig. 1: Phase diagram between l and ρ

The purpose of this research is to demonstrate that super-fixed peg arrangements are not, *per se*, the key to financial discipline and growth. Sustainability of any peg, often invoked for price stability, cannot be engineered solely through nominal exchange-rate arrangements.

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Data-Driven Assessment of Health Systems: A Machine Learning Approach to Economic Inefficiencies in Oncology.

Giorgia Rivieccio, Francesco Schiavone, Sandro Pignata, Anna Crispo and Anna Pia Di Iorio

Abstract This study investigates diagnostic inefficiencies within a regional oncology network, with a focus on the economic costs generated by inappropriate diagnostic pathways. Using patient-level data, we estimate inefficiency-related costs arising at different stages of the diagnostic process, both before and after multidisciplinary team evaluations. A Multilayer Perceptron (MLP) regression model is employed to capture complex non-linear relationships across organizational, sociodemographic, and clinical factors. The results highlight organizational delays, especially in the pre-multidisciplinary phase and geographical distance as key drivers of diagnostic cost inefficiencies.

Key words: Artificial Intelligence, Oncology Networks, Machine Learning, Multilayer Perceptron, Health Economics.

1 Introduction

In recent decades, healthcare systems have increasingly relied on network-based organizational models to improve efficiency, appropriateness, and quality of care.

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Regional oncology networks represent a prominent example of this transition, as they aim to coordinate multiple specialized centres to reduce duplication, delays, and unnecessary diagnostic procedures [2]. However, despite their potential benefits, inefficiencies persist, particularly in the diagnostic phase, where repeated or non-guideline-compliant examinations generate avoidable economic costs. Understanding and predicting these diagnostic inefficiencies is especially relevant in contexts characterized by resource constraints and organizational fragmentation, which are common features of healthcare systems undergoing economic and institutional transition. From a policy perspective, identifying the drivers of inappropriate diagnostic costs can support targeted interventions that improve efficiency without compromising clinical outcomes [1]. This study contributes to this literature by developing a predictive and interpretable statistical framework to model diagnostic inefficiency costs within the Campania Oncology Network (ROC). Specifically, we apply a Multilayer Perceptron (MLP) to predict the economic costs associated with inappropriate diagnostics and to uncover the key organizational, clinical, and sociodemographic factors driving these costs.

2 Sample data and methodology

This study uses data from the ValPeROC project, a multidisciplinary initiative launched in 2020 by the IRCCS National Cancer Institute "Fondazione G. Pascale" and the VIMASS Lab at the University of Naples Parthenope. The dependent variable captures the cost of diagnostic inefficiencies, defined as expenditures associated with unnecessary, duplicated, or non–guideline-compliant diagnostic tests. These costs primarily arise during two stages of the diagnostic pathway: the Pre-GOM phase, defined as the period from symptom onset or initial diagnosis to the first Multidisciplinary Tumor Board (MTB; hereafter referred to as GOM) visit, and the GOM phase, spanning from the first MTB visit to the initiation of treatment.

Following complete-case analysis, the final dataset comprises 984 cancer patients observed over a three-year period, covering the entire diagnostic pathway within the regional oncology network.

Given the highly non-linear nature of diagnostic processes, traditional linear models may fail to capture complex interactions between patient characteristics, organizational factors, and geographical constraints. We therefore adopt a Multilayer Perceptron (MLP), which provides a flexible functional approximation of the underlying cost-generating mechanism.

The dataset is randomly split into training (80%) and test (20%) sets. Continuous covariates—namely age, years of schooling, distance to the treatment center (in kilometres), and Pre-GOM duration (in days)—are min–max normalized using parameters estimated on the training set, as the target variable.

The MLP maps patient-level covariates to a continuous prediction of diagnostic inefficiency costs through a sequence of linear transformations and nonlinear activation functions. The network architecture consists of two hidden layers with 32 and 16 units, respectively, both using the tanh activation function, followed by a

linear output layer, consistent with the regression nature of the task. To mitigate overfitting, dropout (rate = 0.5) is applied after each hidden layer. Model training is performed using the Huber loss function ($\delta = 0.1$), which is well suited to the right-skewed and heavy-tailed distribution of diagnostic costs, as it balances sensitivity to small errors with robustness to outliers. Optimization is carried out using the Adamax optimizer with a learning rate of 0.002 and batch size 16. Early stopping with a patience of 30 epochs is employed based on validation loss, using a validation split of 20% within the training set.

For benchmarking purposes, we also estimate a Random Forest model using the same training and test splits and identical preprocessing of the covariates. Model performance is evaluated on the test set using standard forecasting error metrics—MAE, MSE, and RMSE—computed on predictions back-transformed to the original cost scale.

3 Results

To benchmark predictive performance, we compare the MLP with a Random Forest using a 25-fold stratified cross-validation. Both models are trained and evaluated on identical folds, with normalization performed within each training set to avoid data leakage.

Table 1: Model comparison

Model	***MAE***	***MSE***	***RMSE***
Random Forest	176.29 ± 28.47	72822.36 ± 49762.38	258.06 ± 80.52
Batch size	159.97 ± 29.07	72662.36 ± 52932.35	255.27 ± 88.35

The MLP achieves lower Mean Absolute Error (MAE) and slightly lower Root Mean Squared Error (RMSE) on average.

Training curves exhibit smooth convergence with no evidence of divergence, confirming the stability of the learning process despite the moderate sample size.

The global feature importance plot, reported in Figure 1, highlights Pre-GOM duration and distance to the treatment center (in kilometres) as the strongest predictors of diagnostic inefficiency costs, followed by age, years of schooling, and—among clinical variables—the symptomatic diagnostic modality.

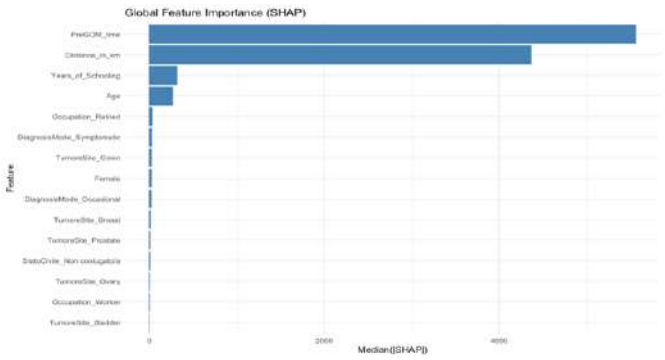

Figure 1: Global Feature Importance plot (SHAP)

Non-linear relationships between Pre-GOM duration and inappropriate diagnostic costs are captured by SHAP dependence plot. In the first months of delay, costs increase rapidly, identifying a critical time window in which delays become prolonged but are not clinically justified. During this phase, the model predicts the highest risk of diagnostic inefficiencies. This critical window is particularly relevant from a policy and healthcare management perspective, as it identifies the period in which targeted interventions—such as accelerated referrals or earlier multidisciplinary evaluation—could have the greatest impact in reducing unnecessary diagnostic expenditures. Distance to the treatment center also exhibits a non-linear pattern, diagnostic inefficiency costs initially increase with distance but decline for patients living very far from specialized centres. Age shows a clear, monotonic negative association with inappropriate costs. Younger patients appear to experience a higher risk of costs due to inefficient exams. Symptomatic diagnosis is also associated with a small increase in inefficient costs compared to the reference category of screening. This result is consistent with the fact that symptomatic pathways are often less structured, more urgent, and may involve a wider variety of initial diagnostic tests before the patient reaches a specialized center. Screening pathways, by contrast, follow a highly standardized protocol, which naturally reduces variability and the likelihood of unnecessary or repeated exams.

In conclusion, economic inefficiencies along the diagnostic journey within oncology networks are primarily driven by organizational delays, geographical distance, and selected patient characteristics. The Multilayer Perceptron provides a flexible and robust modelling framework capable of capturing complex non-linear relationships while remaining interpretable through SHAP analysis. From a policy perspective, the identification of critical delay windows and high-risk patient profiles offers actionable insights for reducing unnecessary diagnostic costs, particularly in healthcare systems facing economic and organizational transition.

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Daughters of a lesser God. Harassment and violence in the workplace. A survey in the Bologna area of Italy

Sergio Brasini, Demetrio Panarello and Giorgio Tassinari

Abstract This paper investigates the prevalence and correlates of workplace harassment and violence, using data from an online survey conducted in the Bologna area of Italy in 2022-23 and 2024-25, covering a broad range of sociodemographic, occupational and well-being indicators. An Ordered Probit model is employed to examine the factors associated with increasing severity of harassment. Then, a Multiple Correspondence Analysis reveals structured and gendered patterns in the types of harassment experienced across employment contexts. Overall, the findings suggest that workplace harassment remains a widespread phenomenon even in economically and socially advanced areas, underscoring the need for continued monitoring and targeted policy interventions.

Key words: Workplace harassment, Job satisfaction, Ordered probit model, Multiple correspondence analysis

1 Introduction

In contemporary societies, work plays a central and, in many respects, all-encompassing role in shaping individual identity and providing meaning to life [2]. Working conditions and the quality of interpersonal relationships in the workplace are therefore crucial dimensions affecting individual well-being and, more broadly, social equilibrium and collective practices [1]. In recent years, growing attention

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from public opinion, scholars and research institutions has focused on women's working conditions, driven in part by feminist movements and by extensive media coverage of violence and harassment against women.

The web-based survey conducted within the project "Together for the well-being of female workers", designed in close collaboration with the non-profit association Unione Donne in Italia – Bologna, is embedded in this broader context. This contribution examines the main findings of the survey, which was carried out in two waves, in 2022-23 and 2024-25. The investigation involved the collaboration of several local authorities, associations and private companies, which promoted the survey among their employees and supporters, both women and men. In addition to standard sociodemographic characteristics, the questionnaire collected information on health status, job satisfaction, time use, resilience, stress, economic conditions, mobility habits, care work, and experiences of violence or harassment, as well as their consequences and respondents' reactions. Participation was satisfactory, with over 600 completed questionnaires in the first wave and approximately 250 in the second one. To identify the main correlates of negative experiences in the workplace, an Ordered Probit regression model is estimated. Then, a Multiple Correspondence Analysis is conducted on the variables found to be significant in the regression model, to explore the underlying associative patterns among respondents' characteristics and experiences of workplace harassment.

2 Data and Results

With regard to violence and harassment against women in the workplace, including psychological, physical and sexual forms, the relative frequency observed in our sample (40.7%) is slightly higher than that reported by Istat [5] in its most recent survey (31.9%), by the International Labour Organization [4] in its worldwide survey (30.0% of women in Europe and Central Asia) and by Eurostat [3], which reports a prevalence of 30.8%. Given that these surveys cover different geographical areas and adopt partially different definitions of harassment, the results of our study can be considered broadly consistent with those emerging from such investigations.

Our sample is predominantly composed of women, with only 13.0% of questionnaires completed by men. Most respondents are married or cohabiting (68.8%), aged between 30 and 59 years (82.4%) and have children (63.0%). About 27.9% of respondents are employed in the public sector, 67.5% in the private sector and 4.6% are self-employed or not currently employed.

Psychological harassment emerges as the most widespread form of violence, reported by 36.2% of respondents. This is followed by verbal harassment (19.7%), physical harassment (7.3%) and sexual violence (3.2%). Additional noteworthy findings concern the fact that a non-negligible share of men (23.4%) report having experienced episodes of violence or harassment, and the strong negative association between exposure to harassment at work and job satisfaction.

An Ordered Probit regression model is estimated to investigate the determinants of harassment severity. The dependent variable is defined as the most severe type of

harassment or violence experienced by the respondent, ordered as follows: 0 for no harassment, 1 for verbal harassment, 2 for psychological harassment, 3 for physical harassment, and 4 for sexual harassment. The explanatory variables include gender (0: male; 1: female), age group (1: 16-29; 2: 30-44; 3: 45-59; 4: 60 or older), number of children (capped at 4), type of employment (0: private sector, self-employed or no job; 1: public sector) and cohabitation status (0: not married or cohabiting; 1: married or cohabiting). The regression results, reported in Table 1, indicate that being a woman is associated with a higher probability of experiencing more severe forms of harassment. Conversely, employment in the public sector and being married or cohabiting are negatively associated with harassment severity. Older age groups and a higher number of children also display negative associations, although these effects are estimated with low levels of statistical significance.

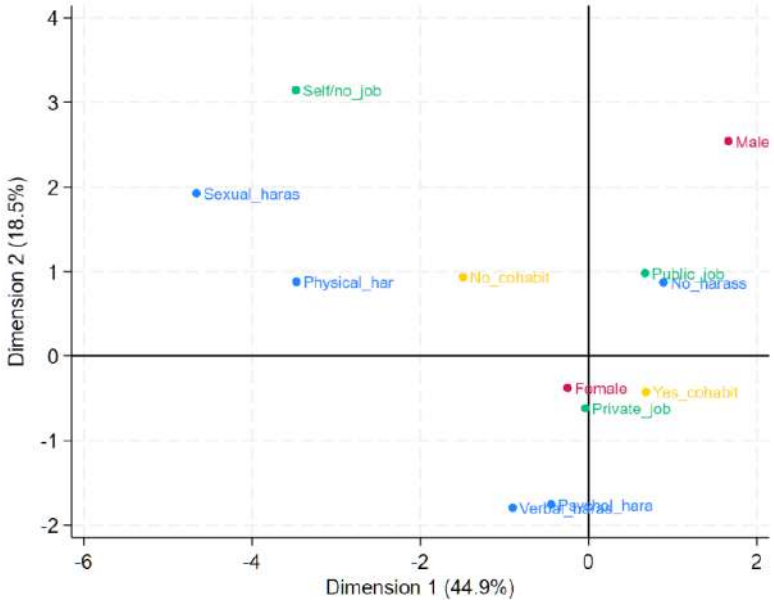
Table 1: Ordered Probit results (dependent variable: most severe type of harassment experienced)

Variable	***Coefficient***	***Standard Error***
Female	0.536***	0.132
Age group	-0.036	0.056
Number of children	-0.013	0.046
Public employment	-0.230**	0.091
Married or cohabiting	-0.284***	0.088

Notes: ** p<0.05; *** p<0.01. Cut-points not shown. Observations: 853.

To further explore the relationships among the significant variables identified in the regression analysis, a Multiple Correspondence Analysis (MCA) is conducted. As shown in Figure 1, the first two dimensions explain 63.4% of total inertia, providing a meaningful representation of the underlying associations. Dimension 1 reflects differences in reported exposure to harassment across gender and employment contexts. It primarily contrasts respondents reporting no workplace harassment, who are more frequently men, employed in the public sector, and cohabiting, with respondents reporting experiences of harassment, particularly physical and sexual ones, who are more closely associated with self-employment or no-job status. Dimension 2 captures gendered patterns in the experienced type of harassment. Verbal and psychological harassment are more strongly associated with women, private-sector employment, and cohabitation, whereas physical and sexual harassment are positioned closer to men and to non-cohabiting respondents with self-employment or no-job status. Overall, the MCA highlights a structured relationship between gender, employment context and workplace harassment, pointing to a general gradient of exposure and to distinct gendered configurations.

Figure 1: Multiple Correspondence Analysis coordinate plot



3 Conclusions

The evidence presented in this study can be interpreted as an "extreme case", as it reflects the situation in the Bologna area, one of the most economically, socially and civically advanced districts in Italy. It is therefore reasonable to assume that the problem of workplace harassment and violence may be even more severe in less advantaged areas of the country. While the survey successfully achieves its general objective of shedding light on the prevalence and correlates of workplace harassment, further investigation is needed to obtain a more comprehensive understanding of the phenomenon. Although the exact magnitude of the problem cannot be precisely quantified, especially given the well-known difficulties victims face in reporting experiences of violence, the results clearly indicate that harassment and violence in the workplace are far from rare and represent a significant issue for workers' well-being and job satisfaction.

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Decoding Websites: Inferring Financial Distress in SMEs from Coding Style

Carlo Bottai, Lisa Crosato and Caterina Liberati

Abstract This paper proposes to examine whether financially distressed Small and Medium-sized Enterprises display distinctive latent coding styles in their websites compared with healthy firms. By leveraging a large dataset of HTML tags from corporate homepages, the study aims to investigate structural and technical design features as potential indicators of financial conditions. The research hypothesizes that specific website configurations may correlate with financial vulnerability, suggesting that technical website design could serve as a novel, non-financial signal of distress. By combining web analytics with statistical modeling, this study seeks to contribute to the growing literature on digital traces as predictors of firm performance.

Key words: SMEs, Financial Distress, HTML Tags, Corporate Websites, Coding Styles.

1 Introduction

Corporate websites have emerged as critical, non-traditional data sources for quantitative analysis of firm behavior, capabilities, and strategies. Beyond their conventional role in marketing, these digital platforms serve as reflections of organizational choices, innovation activities, and market orientation. This utility has spurred

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researchers to analyze websites as rich sources of digital signals that complement traditional corporate data [2, 6, 2, 8] . This analytical interest, which includes studies on website quality, usability, and interactivity [13], has recently extended to investigating the potential financial implications of website features [12, 4, 14, 11].

Our study aims to address whether the latent coding styles of websites belonging to Small and Medium-sized Enterprises (SMEs) experiencing financial distress—defined as market exit within one year—systematically differ from those of financially sound firms. The research is built on the premise that the design structure of SME websites may contain latent signals of economic vulnerability, which this paper seeks to identify and analyze.

2 Data

The study focuses on a sample of SMEs within the Italian manufacturing sector (NACE code C), identified through the Moody's Aida–Orbis database. To ensure the analysis accurately reflects firm-driven digital strategies and independent investment in online presence, the selection is restricted to companies maintaining a dedicated corporate URL. Consequently, firms relying exclusively on third-party platforms or generic social media hosting are excluded from the dataset. The data collection (Fig. 1) and processing follow a systematic multi-step workflow:

- **Data Retrieval**: For each eligible firm, up to twenty web pages are sourced from the 2018 archives of the Internet Archive's Wayback Machine to ensure temporal consistency with the financial data
- **Validation**: To guarantee a robust match between the digital content and the legal entity, websites are cross-validated by verifying the presence of specific identifiers, such as VAT numbers or headquarters addresses, directly on the crawled pages
- **Feature Extraction**: The analysis centers on the homepage as the primary digital touchpoint. The methodology involves the systematic extraction of all HTML tags and their associated attributes to map the latent structural and technical design features of the website.

The identification process yields a large-scale sample of over 42,000 observations, partitioned into *distressed* and *sound* categories based on their 2019 financial status. Following the definitions adopted by [1] [5], firms are classified as distressed if they exited the market due to bankruptcy, liquidation, or insolvency. Conversely, firms remaining active throughout 2019 are categorized as financially sound.

Preliminary comparative analyses–not reported here for the sake of brevity–confirm significant differences between distressed and sound SMEs across both financial and digital dimensions.

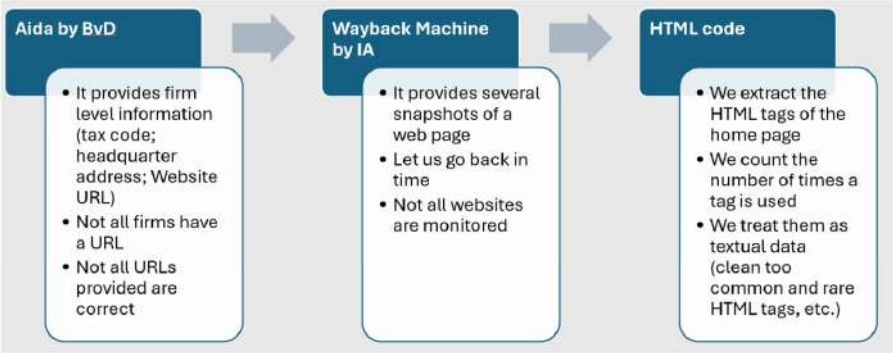

Fig. 1 Data production flow: from URLs to HTML code.

3 Analytical Strategy

To examine whether distressed firms exhibited distinctive technical signatures relative to sound companies, the analysis relied on an analytical framework centered on the latent associative structure of HTML tags. Given the high-dimensional and categorical nature of the data, Multiple Correspondence Analysis (MCA) was employed to project tag presence–absence patterns into a low-dimensional Euclidean space, thereby summarizing the information while filtering out noise. A hierarchical clustering procedure based on Ward's minimum variance method was then applied to the MCA coordinates to identify stable groups of tags that systematically co-occurred across websites, revealing recurrent coding patterns and underlying design structures.

The first component accounted for the majority of the inertia and primarily contrasted older coding practices with more modern ones. The second component explained a substantially smaller share of the inertia and mainly captured differences between the presence and absence of HTML elements. Overall, the resulting factorial space revealed a structured organization of tags, with coherent groupings of legacy elements and systematic absences of widely used basic tags, supporting the interpretation of distinct coding configurations. Subsequently, we obtained a limited number of web design configurations that functioned as non-financial descriptors of firm behavior. The results revealed systematic differences in website characteristics between distressed and sound SMEs. Financially distressed firms were more likely to display shorter and less diverse HTML structures, typically associated with simplified or technologically outdated designs. In contrast, sound firms were disproportionately associated with websites featuring richer content, clearer semantic organization, and higher levels of interactivity. Statistical tests confirmed significant differences between groups and consistent distributional shifts across design configurations. Regression analyses further indicated that financial distress was positively associated with simpler and dated web designs, and negatively associated with more complex and feature-rich configurations.

4 Conclusions

Our study will demonstrate how the HTML structure of an SME's website reflects its financial condition by identifying distinct coding styles across Italian manufacturing firms. It will show that distressed companies will tend to have outdated or poor websites, whereas healthier firms will more often display modern and rich designs. This correlation will persist even after controlling for standard financial indicators, meaning web data will serve as an independent early warning signal. Although the research will be limited by incomplete archives and firms without websites, this information will usefully complement traditional accounting figures due to its timeliness.

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Dynamic sustainability of peer-to-peer accommodation: a DP2 composite index for Airbnb supply in Emilia-Romagna

Andrea Guizzardi, Michele Costa and Ercolino Ranieri

Abstract This paper develops a DP2-based composite index to assess the dynamic sustainability of Airbnb-type peer-to-peer accommodation in Emilia-Romagna (Italy). Drawing on a triple-bottom-line framework, Airbnb indicators from AirDNA are mapped into economic, social-pressure, quality/proxy-environmental and optional-management dimensions. Monthly 2021–2024 indices by ISTAT tourism product type reveal marked heterogeneity: cultural and large urban destinations display high but reducing sustainability, mountain areas show low volatile scores with spring troughs and autumn peaks, while maritime and spa resorts worsen in summer.

Key words: Sustainability, Peer-to-peer accommodation, Composite indicators

1 Conceptual Framework and Methodology

The rapid expansion of Airbnb has fundamentally altered accommodation markets, providing authentic and flexible lodging options while simultaneously challenging destination sustainability across economic, social, and environmental dimensions. While P2P platforms generate supplementary income for local hosts, they also risk crowding, displacement, and regulatory gaps compared to traditional hotels. Policy makers require robust tools for ongoing monitoring of this evolution.

This study adopts the triple-bottom-line framework (Elkington, 1998), conceiving sustainable tourism as the simultaneous pursuit of economic viability (profit), social well-being (people), and environmental stewardship (planet). A DP2-based

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This work gratefully acknowledges the support of the ECOSISTER (PNRR) project.

'sustainability index' integrates official territorial data with AirDNA's high-frequency big data into this structure: revenue indicators (ADR, occupancy) proxy host income; inverted density measures (properties/beds per population/surface) capture social pressure; quality metrics (ratings, superhost share, response rate, minimum stay) and management choices (blocked days, flexible rates) incorporate environmental/professional responsibility - all oriented positively (higher = more sustainable) and min-max normalized for transparent aggregation.

Focusing on Emilia-Romagna NUTS-3 destinations classified by official ISTAT tourism products (cultural-heritage cities, maritime and mountain resorts, spa areas, large urban centers), we merge monthly AirDNA listings for 2021–2024 with ISTAT population and area statistics to dynamically track trends and seasonality across heterogeneous local ecosystems, grouping cities by tourism product.

The DP2 method (Pena, 1977) aggregates indicators into a single score by measuring the (normalized and redundancy-adjusted) distance from a "best-practice" reference profile (e.g. sample minima). For each observation *i*, the DP2 score is then obtained by computing the weighted distance between its normalized profile and the reference profile:

$$DP2_i = \sum_{j=1}^{J} \left(\frac{\left| x_{i,j} - x_j^* \right|}{\sigma_j} \right) (1 - R_j^2); \qquad R_1^2 = 0$$

and rescaling it between 0 and 1 so that higher values indicate greater sustainability. Higher DP2 values signal greater sustainability. The DP2 approach offers a relevant advantage for sustainability assessment in peer-to-peer tourism markets with respect to traditional composite-indicator techniques: it relies on endogenous weights derived from the correlation structure of the data, thus avoiding arbitrary weighting schemes and mitigating multicollinearity by downweighting redundant indicators based on (1 minus) their coefficient of determination with prior variables. This feature is particularly important in the Airbnb context, where economic performance, intensity of use and quality attributes are often strongly interrelated. Furthermore, DP2 is well suited (Zarzosa Espina and Somarriba Arechavala, 2013) to capture multidimensional phenomena while preserving interpretability.

To explore the dynamics of peer-to-peer sustainability, monthly $DP2_i$ indices are computed for each product. For every unit, the monthly series is ordered chronologically and a time counter t is defined as the running month since the start of the observation window. To account for seasonal patterns in the composite index, four seasonal dummies - winter (Dec-Feb), spring, autumn and summer – are considered yielding the following specification of the form:

$$DP2_{i,t} = \sum_{j=1}^{4} \beta_{j,i} D_j + \gamma_{1,i} t + \varepsilon_{i,t}$$

The coefficient $\gamma_{1,i}$ captures the direction and strength of the underlying trend (improving or deteriorating sustainability), while coefficients β_j represent the seasonal effects. Statistical significance of the trend is assessed via conventional t-tests. This model allows the paper to distinguish between high but eroding sustainability (high β_j, negative γ_i), low but improving sustainability (low β_j, positive γ_i), and systems where P2P sustainability is essentially stagnant.

2 Data and Results: Heterogeneity Across Tourism Products

This approach yields striking heterogeneity in both sustainability levels and dynamics across tourism product types. Cultural/landscape municipalities and large multidimensional cities achieve the highest DP2 scores (see table 1), remaining seasonally stable with mild negative trends over time. These mature markets have successfully integrated P2P into diversified tourism ecosystems, though gradual listing accumulation and price escalation are slowly eroding social and quality margins, signaling proximity to saturation limits.

Table 1: Seasonal levels and linear trends of the DP2 sustainability index for peer-to-peer accommodation, by main tourism product type.

Destinations by tourism product	Winter	Autumn	Summer	Spring	t
Cultural and landscape m. (mixed vocation)	0,358	0,366	0,356	0,356	-0,0018
Maritime–cultural municipalities	0,139	0,152	0,139	0,121	0,0019
Maritime municipalities	0,174	0,159	0,148	0,159	
Mountain–cultural municipalities	0,172	0,193	0,171	0,126	-0,0019
Mountain municipalities	0,072	0,096	0,069		
Spa tourism municipalities	0,269	0,231	0,236	0,274	0,0020
Other tourist municipalities	0,296	0,279	0,288	0,295	0,0016
Large cities (with multidimensional tourism)	0,326	0,315	0,301	0,319	-0,0016

By contrast, mountain destinations record the lowest levels alongside extreme intra-annual volatility. Spring troughs emerge from intrusive off-season P2P activity on local infrastructure not calibrated for tourism pressure - closed services and limited management capacity amplify even modest listings into disproportionate social and environmental stress. Autumn peaks reflect better alignment with selective nature-based demand (hiking, wellness) that respects carrying capacity, enabling superior quality standards and flexible conditions.

Maritime and spa resorts present a distinct pattern: systematic summer deteriorations driven by capacity strain from high prices and intense utilization, despite solid winter/shoulder performance. Maritime-cultural hybrids show positive trends through diversification buffering peak pressures, while mountain-cultural areas maintain elevated averages yet negative trajectories, as cultural attractiveness accelerates stress faster than governance adjusts.

Overall, the estimated patterns indicate that sustainability trajectories are shaped by the interaction between tourism product and seasonality. The timing and intensity of short-term deteriorations differ markedly across tourism products, and are often concentrated in specific seasons, rather than reflecting a permanent decline in sustainability. As a result, the same destination can alternate between relatively sustainable and fragile patterns over the year, highlighting the importance of a dynamic interpretation of composite sustainability scores.

3 Conclusions and Policy Implications

This paper develops a DP2-based composite index to monitor Airbnb-type accommodation sustainability in Emilia-Romagna, integrating high-frequency AirDNA platform data with a tourism-product classification and triple-bottom-line framework. Methodologically, the approach demonstrates DP2's adaptability to platform-based data, effectively capturing both pronounced seasonal fluctuations and medium-term trajectories in peer-to-peer accommodation performance.

The empirical patterns reveal how local tourism products fundamentally shape P2P sustainability. Cultural/landscape destinations and large cities sustain the highest index levels, yet exhibit gradual weakening that signals proximity to social and qualitative saturation points in these mature markets. Mountain areas, conversely, maintain structurally low scores with extreme seasonal volatility, underscoring inherent fragility where even modest P2P expansion generates disproportionate resident and environmental stress. Maritime, spa, and “other municipalities” occupy intermediate positions where economic and management drivers predominate, offering policy leverage to influence trajectories through operational rather than volumetric controls. Targeted policy recommendations emerge.

Cultural cities and urban centers need tools that stabilize or reduce P2P pressure while raising host professionalism to achieve high-quality, low-impact hosting and appropriate minimum stays. Mountain and maritime destinations require seasonality management with availability aligned to local carrying capacity and incentives to distribute demand off-peak. In both cases, targeted host training on service standards and conscious platform use is central to sustainability. Spa and "other tourist" municipalities suit sustainability charters given their positive sustainability trends.

A governance-centric perspective reframing platforms not as inherent threats but as integrable components of local tourism systems is required. The DP2 methodology facilitates this transition by enabling continuous, evidence-based monitoring for adaptive, product-tailored regulation. Destinations gain a dynamic dashboard for real-time sustainability assessment, supporting proactive adjustments rather than post-hoc prohibitions.

Methodological limitations warrant acknowledgment: environmental aspects receive only indirect proxy treatment through quality metrics; the analysis centers supply-side indicators, potentially overlooking demand-side or resident impacts. Future extensions could incorporate resident perspectives and housing data, refining adaptive governance for sustainable P2P integration.

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Environmental Indicators and Mortality for a Sustainable Growth Prospective

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Abstract This study examines the relationship between environmental indicators and mortality rates as metrics for sustainable growth. Using daily pollution data and mortality records from Puglia, Italy, we apply Gompertz and Cox proportional hazards models to quantify health impacts. Our findings reveal significant associations between PM10, NO2 levels and mortality, with differential effects by gender. The results provide evidence for integrating environmental health indicators into sustainable growth frameworks, highlighting the importance of air quality management for sustainable development.

Keywords: Environmental Indicators, Survival Models, Sustainable Growth, Mortality

1 Introduction

Sustainable growth represents a multidimensional challenge requiring integrated monitoring systems that encompass economic, social, and environmental dimensions. While traditional economic indicators dominate policy discussions, environmental health metrics remain underutilized in sustainable growth assessments.

The United Nations Sustainable Development Goals (SDGs), particularly Goal 3 (Good Health and Well-being) and Goal 11 (Sustainable Cities and Communities), emphasize the interconnection between environmental quality and human health. This study contributes to this discourse by analyzing air pollution indicators as determinants of population health, proposing a framework for integrating environmental health

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metrics into sustainable growth monitoring.

Using high-frequency data from Puglia, Italy, we examine how real-time environmental indicators can inform sustainable development policies and provide early warning systems for public health risks.

2 Methodology

We utilized daily data (2018-2024) from ARPA[1] Puglia monitoring stations, including: PM10, PM2.5, NO2, O3, and SO2 concentrations.
The mortality data were collected from the ISTAT[2] website and processed in R-cran on a daily scale stratified by gender and municipality.

The statistical models is in three complementary approaches were employed:

- Gompertz model: For baseline mortality estimation incorporating environmental stressors
- Cox proportional hazards: Gender-stratified analysis of mortality risk
- Principal Component Analysis: Dimension reduction of environmental indicators

The Gompertz model identified significant associations between lagged pollution exposure and mortality. PM10 (lag1) showed the strongest effect ($\beta = 0.18$, $p < 0.001$), indicating persistent health impacts of particulate matter.

Table 1: Main significant result Gompertz model – mortality daily and PM10 lag 1 day

	Estimates	***S.E.***	***P.value***
Intercept	0.71144	0.01757	2e-16
Brindisi	0.15471	0,02077	9.4e-14
Taranto	1.09000	0,01881	2e-16
Galatina	-0.8609	0.03961	2e-16
Maglie	-1.5739	0.07244	2e-16

Figure 1: Daily mortality variation vs Pm10 lag 1 day

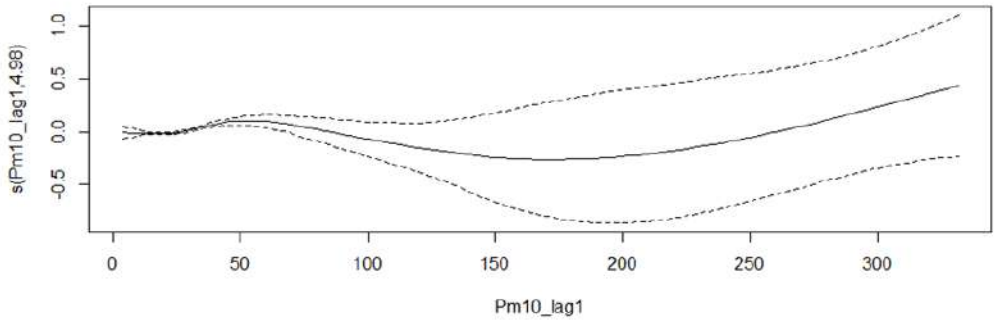


Figure 1 illustrates the estimated non-linear relationship between PM10 concentrations (with a one-day lag) and daily mortality, derived from a Generalized Additive Model (GAM) specification of the Gompertz mortality function, extend by incorporating environmental stressors as time-varying covariates affecting the baseline hazard.

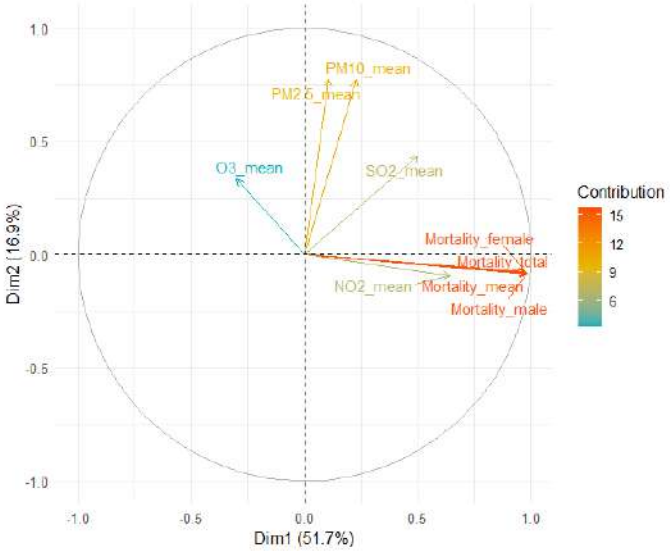
[1] ARPA Puglia, environmental monitoring network- *https://www.arpa.puglia.it/pagina2806_rete-regionale-di-monitoraggio-della-qualit-dellaria.html*

[2] Daily mortality in municipalities by ISTAT *https://www.istat.it/tag/decessi/*

The relationship was estimated using a Poisson regression model with a log link function, specified as:

$$\log(E[Y_{i,t}]) = \beta_0 + f(PM10_{i,t-1}) + \gamma \cdot t + \alpha_i$$

Figure 2: Principal Component Analysis reveals clustering of municipalities by pollution profile



Principal Component Analysis (PCA) serves as a dimensionality reduction technique to identify latent structure in the multivariate pollution-mortality space. This biplot simultaneously represents both municipalities (points) and environmental-health variables (vectors) in the reduced-dimension space defined by the first two principal components, which collectively explain 68.6% of total variance (PC1: 51.7%, PC2: 16.9%).

PCA was applied to the standardized matrix of municipality-level averages for five pollutants (PM10, PM2.5, NO2, O3, SO2) and three mortality indicators (total, male, female). Standardization (z-scores) ensures variables with different measurement scales contribute equally to the analysis and the correlation matrix was decomposed via singular value.

3 Result

The study aims to represent how important it is to use the joint use of general mortality data disseminated and constantly updated by ISTAT, on a municipal basis, and the data of the environmental matrices collected by the ARPA Puglia monitoring network, for the construction of environmental health indicators as components of sustainable growth metrics. The significant associations between air pollutants and mortality, particularly the delayed effects of PM10, suggest that current patterns of economic growth underestimate the costs of environmental health. Gender-differentiated effects are in line with existing literature on biological susceptibility and exposure patterns. From a methodological point of view, the integration of high-frequency environmental data with health outcomes provides real-time monitoring capabilities essential for adaptive policymaking in the context of climate change and urbanization pressures.

Vector length reflects variable's communality (quality of representation in the reduced space), while the cosine of the angle between vectors approximates their correlation: acute angles (<90°) indicate positive correlation, obtuse angles (>90°)

indicate negative correlation, and right angles (~90°) indicate independence.

4 Final remarks

The evidence for incorporating environmental health indicators into sustainable growth assessments. Key contributions include:

- Quantitative links between specific pollutants and mortality risks
- Gender-differentiated vulnerability patterns
- Methodological framework for real-time monitoring

Future research should expand this approach to include additional sustainable growth dimensions (economic resilience, social equity) and explore machine learning techniques for predictive modelling of environmental health impacts.

The biplot reveals three distinct municipality clusters with characteristic pollution-mortality profiles:

1. **High-impact industrial cluster (upper-right quadrant):** Taranto, Brindisi, and Bari exhibit strong positive loadings on PC1, characterized by elevated PM10, PM2.5, and NO2 concentrations, with correspondingly high mortality rates.
2. **Agricultural inland cluster (lower quadrants):** Municipalities such as Altamura and Andria show moderate pollution levels with different compositional profiles. The O3 vector points in the opposite direction from NO2, reflecting the well-documented atmospheric chemistry trade-off where ozone formation consumes nitrogen oxides in photochemical reactions.
3. **Salento peninsula cluster (central-left):** Municipalities including Galatina and Maglie demonstrate lower pollution burdens and correspondingly lower mortality rates, as reflected in their negative coordinates on PC1.

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ESG Factors and Asset Allocation: Evidence from Simulated Portfolios

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Abstract Over the past two decades, corporate Environmental, Social, and Governance (ESG) factors have received growing attention from both theoretical, institutional, and retail investor perspectives. So far, empirical evidence on the actual impact of ESG integration in portfolio construction remains mixed, and its effectiveness continues to be debated in the literature. This study analyzes portfolios composed of fully balanced portfolios, including five low-, five medium-, and five high-ESG-risk assets. To mitigate the impact of asset selection, we simulate 10,000 such portfolios, each built from a random subset of the top 200 NASDAQ constituents by market weight.

Key words: ESG, Global Minimum Variance, Portfolio Optimization, Dynamic Conditional Correlation

1 Introduction

In the last two decades, interest in sustainable investments has significantly increased among both retail and institutional investors [7]. Among sustainable investment strategies, those based on Environmental, Social, and Governance (ESG) factors are among the most widely adopted. As investors are increasingly encouraged to incorporate ESG considerations into their investment decisions—consistent with the first United Nations Principle for Responsible Investment—allocating cap-

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ital to high-ESG-rated firms may contribute to mitigating systemic spillovers during periods of market stress, as highlighted by [3].

So far, empirical research on the relationship between ESG incorporation and stock market performance has produced mixed results (see, for instance, [1, 4, 2]). In the multivariate framework, the Global Minimum Variance (GMV, [9]) portfolio plays a prominent role (see, among others, [8]), as it provides the most efficient allocation in terms of risk minimization. Apart from the recent contribution of [5], which introduce ESG-based risk constraints in portfolio optimization, the literature has paid little attention to the GMV performance of portfolios composed of assets with heterogeneous ESG characteristics. This paper aims to fill this gap. In particular, we consider a fully balanced portfolio constructed by selecting assets across ESG risk categories, namely five low-, five medium-, and five high-ESG-risk assets. Subsequently, we estimate the conditional covariance matrix using the Dynamic Conditional Correlation (DCC) framework of [6]. To evaluate the weight composition, we formulate the following question:

Research Question Are portfolio weights significantly higher for any ESG category compared to the others under the fully balanced GMV configuration?

This question is crucial to assess whether ESG characteristics act as a systematic driver of portfolio allocation rather than merely reflecting diversification effects.

The remainder of the paper is organized as follows. Section 2 outlines the methodology. Section 3 presents the empirical analysis and provides answers to Research Question.

2 Methodology

The conditional GMV problem is to solve, for each t, the following optimization:

$$\min_{\mathbf{w}_t} \mathbf{w}_t^\top H_t \mathbf{w}_t \quad \text{subject to } \mathbf{w}_t^\top \boldsymbol{\iota} = 1 \text{ and } \mathbf{w}_t \geq \mathbf{0}, \tag{1}$$

where $\mathbf{w}_t$ is the $k \times 1$ vector of portfolio weights at time t, H_t is the $k \times k$ conditional covariance matrix at time t obtained from the DCC model, $\boldsymbol{\iota}$ is a $k \times 1$ vector of ones, the first constraint enforces full investment, and the second prohibits short selling. The unique solution to this quadratic optimization problem can be shown to be $\mathbf{w}_t^* = (\boldsymbol{\iota}^\top H_t^{-1} \boldsymbol{\iota})^{-1} H_t^{-1} \boldsymbol{\iota}$, where $\mathbf{w}_t^*$ is the vector of GMV portfolio weights at time t, and contains the optimal weights for each of the k assets, denoted as $w_{1,t}^*, \ldots, w_{k,t}^*$.

The overall weight assigned to ESG category $c \in \{\mathrm{L}, \mathrm{M}, \mathrm{H}\}$–standing for Low, Medium, and High ESG risk, respectively–is obtained by summing the weights of all assets belonging to category c, that is:

$$w_t^{*,c} = \sum_{i \in \mathscr{C}_c} w_{i,t}^*, \tag{2}$$

where $\mathscr{C}_c$ is the set of asset indices classified under ESG category c. To address the research question, we estimate the following regressions:

$$w_t^{*,L} - w_t^{*,M} = \beta_0^{(1)} + \varepsilon_t^{(1)}; \tag{3}$$

$$w_t^{*,L} - w_t^{*,H} = \beta_0^{(2)} + \varepsilon_t^{(2)}; \tag{4}$$

$$w_t^{*,M} - w_t^{*,H} = \beta_0^{(3)} + \varepsilon_t^{(3)}, \tag{5}$$

where $\varepsilon_t^{(j)}$, with $j = 1,2,3$, is the regression error term. Each equation tests whether the average difference between two ESG-weighted components is statistically different from zero, using a regression with only an intercept.

Definitions (Def.) 1–4 of ESG risk category dominance, reported in Table 1, are used to test the research question. For instance, Definition 1 identifies Low ESG risk dominance, which arises when assets classified as Low ESG risk receive significantly higher average portfolio weights than both Medium and High ESG categories.

Table 1 Definition of ESG Risk Category Dominance

Def.	Dominant ESG Category	$\beta_0^{(1)}$ (Low vs Medium)	$\beta_0^{(2)}$ (Low vs High)	$\beta_0^{(3)}$ (Medium vs High)
1	Low ESG Risk	> 0 (significant)	> 0 (significant)	–
2	Medium ESG Risk	< 0 (significant)	–	> 0 (significant)
3	High ESG Risk	–	< 0 (significant)	< 0 (significant)
4	No dominance	not significant	not significant	not significant

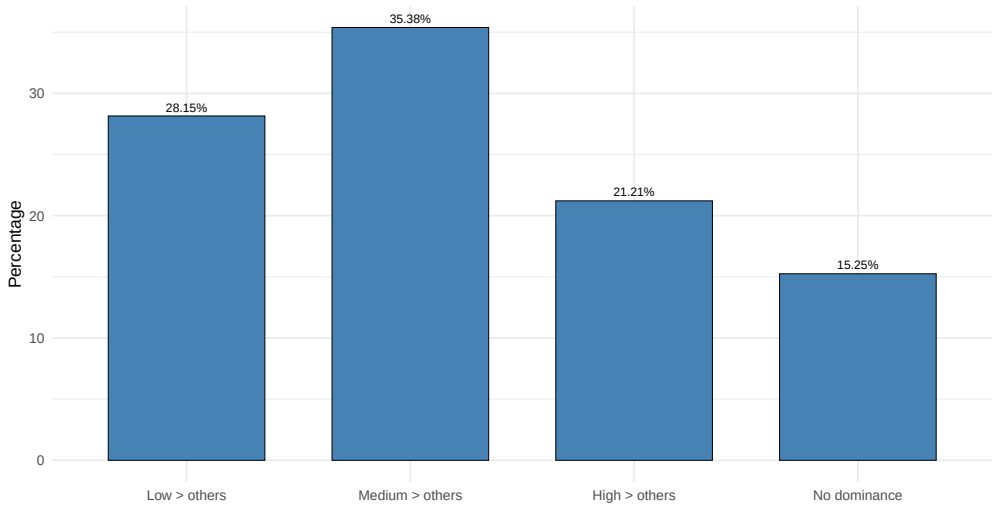
3 Empirical Analysis

The assets under investigation are drawn from the top 200 NASDAQ constituents by market capitalization. The sample period spans from January to December 2024, totaling 252 daily observations. To mitigate the impact of asset selection on portfolio composition, we randomly select the assets for each ESG-based category 10,000 times. The percentage of cases in which the definitions in Table 1 apply across the 10,000 simulated portfolios is reported in Figure 1.

Definition 2 in Table 1, corresponding to Medium ESG Risk dominance, identifies the case in which the Medium ESG assets exhibit significantly higher average weights relative to both Low and High ESG assets. This dominance pattern represents the most frequent outcome (35.38%), followed by High ESG Risk dominance (21.21%), while no dominance occurs least often (15.25%).

Overall, these findings indicate that, under the GMV criterion, assets characterized by a Medium ESG Risk profile are the most likely to dominate in terms of

Fig. 1 Barplot of the percentage of dominance for each ESG category in the fully balanced GMV portfolio across the 10,000 simulations.



Notes: The plot illustrates the percentage of dominance, across the 10,000 simulations, of each ESG category in the fully balanced GMV portfolio.

portfolio weights within a fully balanced portfolio, for the data and period under consideration.

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From National Economic Accounting to Well-being Accounting: SNA 2025 as a Starting Point for a Homogeneous and Coherent Assessment

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Abstract: The evolution of the System of National Accounts toward a well-being accounting framework represents a gradual process aimed at overcoming the structural limitations of Gross Domestic Product as a synthetic indicator of economic and social progress. National accounting was historically designed to measure production, income, and expenditure, providing a statistical infrastructure for macroeconomic analysis and policy design. The forthcoming SNA 2025 revision strengthens the role of national accounts as a central statistical framework capable of integrating additional information relevant for the assessment of well-being and sustainability. This paper discusses the transition toward a multidimensional well-being accounting perspective and highlights the role of household-centered indicators, distributive national accounts, and the evaluation of non-market services through shadow pricing approaches such as willingness-to-pay.

Keywords: National accounts, well-being accounting, SNA 2025, shadow pricing

1 Introduction

In recent years, the debate on how to measure economic progress has increasingly highlighted the limitations of traditional macroeconomic indicators. Gross Domestic Product (GDP) remains an essential measure for analysing production and economic

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dynamics, but it is widely recognised that it cannot fully capture the broader concept of social well-being. As economies become more complex and societies reach higher levels of development, income increases do not necessarily translate into corresponding improvements in living conditions, quality of life, or sustainability. In this context, the forthcoming revision of the System of National Accounts (SNA 2025) represents an important step in strengthening the analytical role of national accounting. Rather than replacing the traditional framework, SNA 2025 aims to expand its informational capacity by developing thematic and extended accounts and placing greater emphasis on the household perspective. This paper discusses how this evolution can contribute to a more coherent framework for well-being accounting, highlighting the role of national accounting aggregates and complementary evaluation approaches for assessing the quality and welfare impact of non-market services.

2 National accounting does not measure well-being

The evolution of the System of National Accounts toward a well-being accounting framework, in recognition of the structural limitations of Gross Domestic Product as a synthetic indicator of economic and social progress, represents a complex and gradual process. National accounting was historically conceived as a tool for measuring production, income, and aggregate expenditure, proving essential for macroeconomic analysis and for supporting economic policy decisions. The System of National Accounts was originally income-centered for historical reasons (Marshall Plan), but in the immediate post-war period, producing income also meant producing well-being. Once a certain level of affluence was reached, the coincidence between income and well-being weakened (Antolini, 2016), since marginal increases in income do not necessarily translate into improvements in well-being, especially in its subjective component. Over time, adjustments have been introduced without modifying the definition of production itself (Antolini, 2016). The concept of investment has instead been broadened (SNA 1993; SNA 2008), and tertiary income distribution at the level of institutional sectors has been introduced through aggregates such as adjusted disposable income and actual final consumption. Already Kuznets observed that “The welfare of a nation can scarcely be inferred from a measurement of national income” (Kuznets, 1934), emphasizing the structural limits of GDP from the very origins of national accounting. The Report by the Commission on the Measurement of Economic Performance and Social Progress (Stiglitz, Sen and Fitoussi, 2009) represented a turning point in the international debate, continuing the path initiated by the OECD (2007) and by reflections from the 1970s (Ruggles and Ruggles, 1973). The Report stresses that GDP cannot capture fundamental dimensions of well-being, such as income distribution, quality of life, sustainability over time, and the contributions of non-market activities. In parallel, theoretical contributions such as Grice (2011) have highlighted how national accounts already contain potentially relevant information for well-being analysis, provided they are used in a more articulated way and complemented by additional accounting frameworks. Institutional sector accounting analysis, particularly concerning households, is

strategically relevant for measuring redistribution activity within the economy. As well as Grice stresses the importance of evaluating public services beyond the simple input=output scheme. The OECD (2024; 2025) has conducted experimental studies to adjust GDP by integrating income distribution into national accounting, using household microdata. The integration of **microdata into national accounting** is increasingly important for enriching the statistical foundations of national accounts and improving the analysis of well-being. Within the revision process of **SNA 2025**, the Well-being and Sustainability Working Group proposes the development of **thematic and extended accounts** that complement the traditional framework without redefining it. These extensions emphasize the **household perspective**, distributive accounts, and indicators such as disposable and adjusted disposable income. Moreover, the framework adopts a **capital-based approach to sustainability**, linking wealth stocks and environmental accounts (SEEA) and highlighting the importance of **net measures of income and production**.

3 The importance of service quality

Within the **SNA 2025 framework**, non-market services such as health and education are still valued mainly through production costs in traditional national accounts. However, the introduction of **thematic and extended accounts** allows the consideration of welfare gains related to service quality. In this context, **shadow pricing and willingness-to-pay (WTP)** methods can be used to estimate the monetary value of improvements in public services and citizens' well-being, beyond the traditional approach (output=input) WTP thus allows the monetization of improvements in terms of quality, accessibility, and effectiveness, providing a complementary measure of economic well-being.

Table 1: Synthetic data for evaluation for Health care digitalization process

ID	*Annual income (€)*	*Uses digital health services (0/1)*	*Time saved (hours/year)*	*Perceived quality improvement (1-10)*	*Annual WTP (€)*
1	20000	1	20	7	90
2	35000	1	15	8	130
3	50000	1	12	9	180
4	18000	0	5	5	40
5	42000	1	18	8	160
6	27000	1	10	6	95
7	60000	1	8	9	210
8	22000	0	6	5	55
9	48000	1	16	8	170
10	30000	1	12	7	120

The econometric specification in this case is (coefficient value in bracket):

1] *WTPi*=β0 *(-34,5)*+β_1*(0,002***)*Income+β_2 *(21,8**)* DigitalUse+β_3 *(2,05**)* TimeSave+β_4 *(11,30***)* Quality+εi

R^2 = 0,87 Adjusted R_2= 0,82; Significance level: ***p<0.01,** p<0,05

While the welfare gain is due from:

2] Welfare Gain =WTP medio×population using digital data

For example, if the estimated average willingness to pay is approximately 125 euros per year and the number of users of digital health services is one million, the total welfare gain would be approximately 125 million euros annually. This simple exercise illustrates how microeconometric evidence can be integrated into extended well-being accounts within the SNA 2025 framework. Anyway, shadow valuation may also be extended to volunteering activities. Volunteer work, being unpaid and lacking a market price, remains excluded from official GDP measurement, despite generating implicit economic value and contributing to essential collective services. In such contexts, volunteer work may be accounted for through imputed valuation approaches—such as the replacement cost method—within satellite accounts dedicated to non-profit institutions and well-being.

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From Training to Employment: An Evaluation of the ESF 2014–2020 Vocational Training Programme in Aosta Valley

Alessia Juglair, Consuelo Rubina Nava and Alessandro Riccardo Novallet

Abstract Policy evaluation is central to assessing the efficiency of programmes such as those financed by the European Social Fund (ESF), whose primary objective is to support initiatives that enhance participants' skills and knowledge, facilitate their entry into the labour market, and promote social inclusion. Despite its relevance, empirical and methodological contributions in this area remain limited. Thus, using a dataset on vocational training courses funded under the ESF 2014–2020 programme in the Aosta Valley region, this paper applies both classical and Bayesian logistic regression models to evaluate its efficiency. Preliminary results suggest that effective training policies to increase employment must consider multiple and interacting factors.

Key words: Logistic regression, Bayesian methods, policy evaluation, European Social Fund, employment outcomes, vocational training.

1 Introduction

In recent decades, policy evaluation has become a central tool for guiding public-decision making, generating empirical evidence on the effectiveness of interventions and supporting the design of more targeted policies [1]. Although evaluation prac-

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tices are now widespread globally, no single standardized approach exists, as methods vary substantially across countries and contexts. This diversity reflects the complexity of contemporary policymaking, increasingly characterised by multiple actors and plural perspectives [9]. A relevant policy evaluation domain is training policies. The latter aim to develop skills and knowledge directly applicable to the labour market, complementing formal education by equipping individuals with practical and professional competences [6]. Vocational training is strongly supported by EU funds, notably the European Social Fund (ESF), which finances programmes to enhance employability and social inclusion, generating both short-term skill improvements and long-term benefits in terms of competitiveness, innovation, and inclusion. Methodologically, evaluating training policies is challenging, as observational studies must address causal inference issues, typically using propensity scores, matching techniques, and regression methods to control for differences between treated and untreated groups [7]. Recent advances in supervised machine learning provide additional tools to capture complex patterns and non-linear relationships in employment outcomes, complementing traditional econometric approaches, although they require careful adaptation to the casual framework [8].

To explore the potential of combining classical and Bayesian econometric models, this paper consider as a test-bed the ESF 2014–2020 training interventions in the Aosta Valley. Using a rich administrative dataset, the study evaluates post-training employment outcomes and investigates the factors influencing labour market integration.

2 ESF 2014-2020 Programme in Aosta Valley

The autonomous Aosta Valley region in northwestern Italy is a small Alpine area comprising 74 municipalities, characterized by a mountainous landscape and a strategically important cross-border location. It represents an interesting case study for different reasons. Settlements are mainly concentrated along the Dora Baltea river basin in the valley floor, whereas upland communities face typical mountain disadvantages, such as limited accessibility, dispersed populations, and higher costs for residents and businesses[5]. However, the regional labour market has shown positive trends in recent years. Employment reached about 57,200 in 2024, rising by 0.6%, while unemployment fell to 3.9%, well below the national average. Female employment rates are also higher than the Italian average, indicating a relatively resilient labour force [3]. Nevertheless, structural challenges persist, including seasonal employment patterns, the limited size of the local labour market, and skill mismatches. In Aosta Valley, the ESF 2014-2020 Operational Programme (Investments for Growth and Employment), implemented between 2015 and 2023, aimed to address structural and socio-economic challenges, such as youth unemployment, gender inequalities, and the risk of social exclusion. A significant share of resources (€ 8.013.705,31) was allocated to 79 vocational training projects, targeting both young people at risk of social exclusion - the Not in Education, Employment, or

Training (NEETs) - and adults seeking to upskill or requalify [2, 4]. The training projects targeted employed workers, unemployed individuals, and students in vocational pathways. Resources were focused on sectors aligned with local labour demand, including construction, digital skills, healthcare, hospitality, and business administration. Overall, the programme integrated employment support, social inclusion, and skills development, translating European priorities into interventions tailored to the socio-economic context of the Aosta Valley.

3 Data, Methodology, and Empirical Results

This study analyzes the administrative dataset provided by the ESF Managing Authority and the Regional Economic and Social Observatory, collected through employment surveys conducted between 2021 and 2024. The dataset includes 1435 individuals (63% female and 20% under 30 years old) who participated in ESF-funded vocational training programs.

The empirical analysis combines a classical logistic regression model (logit) with a Bayesian Markov Chain Monte Carlo (MCMC) approach, both showing that prior employment status is the most reliable positive predictor of post-training employment. The findings show a substantial increase in the probability of being employed after seven months for those already employed at the starting point. For the sample considered, neither gender nor country of birth are significant. In contrast, age at course entry has a significant negative effect on employment outcomes: younger participants exhibit higher probabilities of being employed after course completion. Another significant determinant is participation in professionalizing training courses. Programs with a strong practical orientation and a focus on job-specific skills are associated with significantly higher employment probabilities compared to more general or transversal courses. Considering training fields and taking “Transversal Skills” courses as the baseline, the “Commerce”, “Tourism and Hospitality”, and “Transport” sectors show a lower probability of employment. In contrast, the ”Care Services” sector has a significant positive effect, with training in this area notably increasing employment likelihood due to rising demand for care-related skills. Other fields, including “Financial, Insurance, Banking, and Real Estate Activities”, “Construction”, “Craft and Manufacturing Industry”, and “Business Services”, do not show statistically significant effects compared to the baseline.

The consistent results from both methods increase confidence in the findings, identifying prior employment, age at entry, and participation in professionalizing courses as key predictors of short-term employment outcomes, while the Bayesian approach enhances uncertainty assessment through credible intervals.

4 Conclusion

This study analyzed the effectiveness of ESF 2014–2020 vocational training interventions in the Aosta Valley. Using a rich administrative dataset and combining classical logistic regression with Bayesian methods the analysis identified key determinants of post-training employment. Prior labour market experience, age, and participation in professionalizing courses emerged as the most relevant factors, while sectoral effects showed heterogeneous impacts. The convergence of results across methodologies reinforces the robustness of the findings. Overall, the evidence highlights the importance of tailoring training programs to local labour market conditions, integrating practical skills, and considering participants' background to maximize employment outcomes. To further enhance the analysis, several supervised machine learning algorithms could be implemented, including Naive Bayes, Decision Tree, Random Forest, and XGBoost, to explore non-linearities, interactions, and complex predictive patterns. Future research could extend this analysis by applying mixed-effects MCMC models, allowing for a more nuanced understanding of hierarchical and project-level heterogeneity. These insights can inform the design of future regional training policies, ensuring they are both targeted and effective in promoting employability and social inclusion.

Acknowledgements This work was partially funded by the European Union under the PR FSE+ 2021–2027 of the Autonomous Region Valle d'Aosta, Project Code FSE.44406.24AJ.0.0001.PED, CUP B63C24001040008, entitled "Sostenibilità e resilienza nei territori montani: istruzione, economia, disuguaglianza, e autonomie regionali". Specific designation of the research programme: "Valutazione delle politiche e Machine Learning: crescita sostenibile e progresso socioeconomico duraturo della Valle d'Aosta" – UNIVDA/FAR4/03/2024.

The author would also like to sincerely thank Dr. Dario Ceccarelli for his valuable support in the construction of the database and for his assistance throughout the data preparation process.

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Fuzzy Measures of Economic Insecurity Among Households in Three Italian Regions

Giuseppe Verdoliva and Andrea Regoli

Abstract This paper analyses a subjective component of economic insecurity, namely the difficulty in affording daily-life needs as reported by households living in three Italian regions (Lombardy, Tuscany, and Campania).
Adopting a multidimensional perspective on data coming from a sample survey, subjective economic insecurity is measured through fuzzy logic techniques based on proximity measures. The results reveal marked regional and socio-demographic disparities, with single-parent households—especially single mothers—and young single adults facing the highest levels of insecurity, highlighting the relevance of targeted local policy interventions.

Key words: affordability, multidimensional vulnerability, proximity measures, household typology

1 Introduction

In recent years, the concept of economic insecurity has become a central analytical tool for understanding everyday financial difficulties beyond traditional measures of monetary poverty. It refers to a condition of uncertainty experienced by individuals and households about their ability to meet daily-life expenses, keep up with financial commitments, and absorb unexpected economic shocks. From this perspective, the focus shifts from income insufficiency alone to the joint role of affordability of daily-life needs, future expectations, and intertemporal vulnerability.

Recent literature emphasises that economic insecurity is an inherently multidimensional phenomenon, encompassing both subjective elements—such as difficulties in making ends meet or perceptions of inadequate resources—and

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objective indicators linked to adverse events, including income losses, arrears on rent or utility bills, and the inability to cope with unforeseen expenses. In the Italian context, recent analyses based on EU-SILC data show that these dimensions tend to overlap and reinforce one another, generating trajectories of persistent economic fragility as well as marked territorial and socio-demographic inequalities [2, 3, 4, 5].

This paper investigates the perception of economic insecurity among households classified by family type. We follow a multidimensional approach, based on fuzzy logic, where the membership function derives from proximity measures. The empirical application is based on data from a sample survey of over 10,000 households living in three Italian regions (Lombardy, Tuscany, and Campania), within a project aimed at investigating vulnerability at a local level[1].

2 Methods and data

Since the 1990s, fuzzy measures have been widely considered in the analysis of living conditions, as they allow overcoming key limitations of traditional methodologies such as the dichotomy inherent in the use of thresholds [1]. Within the fuzzy approach, vulnerability is assessed through functions that assign each unit a score on a continuous scale ranging from zero to one. These scores represent the degree of membership of each household or individual in the set of vulnerable units. Values closer to one represent quasi-full membership, while values closer to zero represent quasi-non-membership. In this framework, we quantify subjective economic insecurity as the similarity between households and the status that describes the maximum possible vulnerability for a given set of indicators. This allows comparison of each unit's situation with a reference unit reflecting the greatest insecurity, providing a basis for a quantitative assessment of the phenomenon.

Let i be a generic statistical unit. Let h denote the maximum vulnerability status. Let P be a generic proximity measure, then $P(i,h)$ denotes the outcome of the comparison between unit i and the reference status h. The choice of the function to be applied and the status h for comparisons depends on the nature of the available data. With regards to status h, its selection depends on the values taken by the variables and how these affect the proximity: if specific values can be directly associated to maximum vulnerability, they can be used to define status h; otherwise, if vulnerability monotonically influences proximity (e.g. similarity to status h increases as the well-being for a specific item decreases) then the extreme values of the variables—either in their observed or theoretical range—can be considered. Once the membership function values have been computed, they must be synthetised into a composite index. In this regard, we aggregate the values by means of the weighted average, with weights equal to the sample weights.

[1] Measuring inequalitY, PovErty and living cOnditions for Planning Local stratEgies (MYPEOPLE), PRIN Call 2022 PNRR, Ministry of University and Research, https://www.mypeople-unibg.it/mp/index.php

The items that we analyse focus on subjective difficulties in three domains: i) necessary expenses; ii) social life participation and, only for households with children under 16 years old, iii) child-related expenses. These domains reflect specific sectors in which policy can intervene to ensure access to essential services (such as healthcare and housing) at controlled prices, social inclusion, and targeted support for families with children.

The items represent what people struggle with. Regarding necessary expenses, they are about difficulties in paying, among other things, bills, medical care, rent or mortgage. About social life participation, they represent any difficulties in affording a week's holiday, in going to the cinema or theatre and going to a restaurant at least twice a month. In the domain of child-related expenses, the items relate to difficulties concerning, among other things, school, sports and recreational expenses. These items are measured on an ordinal scale. They have three possible responses: often, sometimes, or never, where never means no reported difficulty, or expense not due, or not of interest.

In the following analyses, proximity is computed using Gower's similarity measure [6]. As the metric takes values in the unit interval, similarities can be used directly as membership function values. However, to account for the fact that ordinal response categories are not necessarily equally spaced in terms of vulnerability, each variable was transformed by replacing its values with the corresponding values of the empirical distribution function.

3 Results

Table 1 shows that apparent regional differences emerge across the three dimensions of subjective economic insecurity, by household typology, underscoring the importance of locally tailored policy responses.

With respect to difficulties in managing necessary expenses (Dimension 1) and in participating in social life (Dimension 2), households consisting of a single elderly member are those that declare themselves to be the least vulnerable in every region. They report being able to afford the expenses that are relevant to them more often than other families. When the sole member is under 65, the degree of vulnerability is greater, especially in Campania.

Across all regions, single-parent households are among the most disadvantaged, with single mothers experiencing greater hardship than single fathers. These families are doubly penalised by the absence of a spouse, who generally represents a second source of income necessary to make ends meet, and by the simultaneous presence of dependent children.

The presence of dependent children is highlighted as a risk factor, especially concerning participation in social life. In fact, when it comes to holiday expenses, eating out and going to the cinema/theatre, economies of scale are minimal, if not absent. With reference to these expenses, single-parent families with children are clearly the most vulnerable group in Lombardy and Tuscany. In Campania, both

single mothers with children and single adults under the age of 65 face the greatest difficulties.

Turning to child-related expenses (Dimension 3), single mothers with children face exceptional hardship across all three regions. In Campania, high levels of insecurity are also reported by couples with children and multi-nuclear families.

Table 1: Measures of subjective economic insecurity by region, household typology and dimension

Region	Household typology	(Dim 1) Necessary expenses	(Dim 2) Social life participa-tion	(Dim 3) Child-related expenses
Lombardy	Single person <65	0,191	0,297	-
	Single person >=65	0,145	0,148	-
	Couple without children	0,154	0,279	-
	Couple with children	0,184	0,335	0,241
	Single mother with children	0,275	0,417	0,341
	Single father with children	0,255	0,396	0,306
	Multi-nuclear families	0,226	0,326	0,312
Tuscany	Single person <65	0,200	0,308	-
	Single person >=65	0,106	0,161	-
	Couple without children	0,157	0,256	-
	Couple with children	0,201	0,338	0,255
	Single mother with children	0,276	0,405	0,389
	Single father with children	0,242	0,330	0,357
	Multi-nuclear families	0,241	0,320	0,277
Campania	Single person <65	0,321	0,402	-
	Single person >=65	0,097	0,190	-
	Couple without children	0,232	0,301	-
	Couple with children	0,287	0,388	0,330
	Single mother with children	0,313	0,500	0,334
	Single father with children	0,310	0,307	0,266
	Multi-nuclear families	0,296	0,371	0,347

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Gender differences in occupational outcomes after master's degree: Does a STEM degree moderate the gender gap?

Sergio Longobardi, Giovanni Boscaino, Antonella D'Agostino, Giuliana La Mantia and Andrea Regoli

Abstract This paper analyses gender disparities in the transition from university to work among Italian master's degree graduates. Using AlmaLaurea data (2018-2023) from three universities, we construct two ordinal occupational outcomes one year after graduation. Adjacent category logit models with partial proportional odds are estimated. The results show that women have significantly lower chances than men of entering the labour market, but once hired, their probability of holding a job matching their skills is similar. STEM degrees improve both employment and overall matching outcomes; however, the female disadvantage in labour market entry persists even among STEM graduates.

Key words: University-to-work transition, Gender Gap, STEM, Adjacent Category Logit

1 Introduction

The gender gap in the labour market is a persistent issue affecting access to the labour market, job mismatch, wages, and other factors. Although several positive

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outcomes have been achieved over the last few decades, women still face many issues in obtaining a job and a well-matched, as well as adequately paid, job. In 2024, the employment rate in the EU (aged 20-64) was 75.8%, with a 10.0 percentage point (pp) gap between men (80.8%) and women (70.8%). Italy was among the worst-performing countries, with an overall rate of 67.1% and the widest gender gap in the EU (19.3 percentage points) [2]. Education has a positive impact on the gender gap in the employment rate, but does not eliminate it: at the EU level, the gender gap falls to 4.9 points among graduates (aged 20-64) [2]; in Italy, the gender gap ranges from almost 28 points among those with a low level of education to 19.5 points among high school graduates, reducing to 6.9 points among graduates [3].

A further concern is job mismatch, which can be distinguished into (i) vertical mismatch referring to working in a job that requires a lower (or higher) level of education than one possesses, and (ii) horizontal mismatch, which concerns working in a field that is unrelated to one's degree [4]. In 2024, the EU's over-qualification rate (% of tertiary-educated workers aged 20 to 64 in jobs not requiring tertiary education) was 21.4%, with a slight gender differences (1.3 pp); the Italian rate (21%) was in line with the EU27 average, however, the country had the most pronounced gender gap in the Union: the proportion of overqualified women was 7.7 percentage points higher than that of men [2]. With regard to horizontal mismatch, the AlmaLaurea survey provides a series of indicators based on subjective assessments by employed graduates, allowing for an analysis of the consistency between the studies completed and the work performed. For instance, [5] shows that, among the graduates in 2023, one year after graduation, 60.8% of first-level graduates and 68.2% of second-level graduates who found work consider their degree to be "very effective or effective" in their job.

Drawing on this, the present study advances existing knowledge by investigating gender disparities in university-to-work transition one year after graduation. Accordingly, the university-to-work transition is operationalised as a three-level ordered outcome that distinguishes different levels of alignment between the attained degree and subsequent employment, thereby going beyond a simple employment status indicator. Furthermore, using AlmaLaurea subjective indicators, we consider two alternative dimensions: obtaining a job consistent either with the skills acquired or with the training received during the degree programme. The aim is to examine (i) gender differences in the university-to-work transition and (ii) whether and to what extent having a STEM degree moderates the gender effect on the job outcome.

2 Data and methods

The analysis relies on data from the AlmaLaurea surveys on master's degree graduates at three Italian universities (the University of Naples "Parthenope", Siena, and Palermo), surveyed one year after graduation. The dataset includes information on their demographic characteristics, academic background, and labour market outcomes. The study covers the cohorts from 2018 to 2023. We restricted the anal-

ysis just to graduates from Law, Economics and STEM fields (common to the three universities). The final data consists of 12,018 graduates. In addition, to address non-response bias (30% of no-response, on average), we implemented an inverse propensity weighting adjustment, for the three universities separately. To address the objectives of the analysis, we constructed two ordinal indicators: JSF, capturing Job Skill Fit, and DTF, representing Degree Training Fit, each taking three ordered categories: (1) not employed; (2) employed in a low-skill job (or with low perceived training adequacy); and (3) employed in a high-skill job (or with high perceived training adequacy). The estimation was performed using the Adjacent Category Logit model [1]. This leads to two logit models for each response variable: one comparing (2) with (1) and one comparing (3) with (2). Furthermore, after testing the assumption of proportional odds, we selected a partial proportional odds model, in which the effects of STEM degree and gender can vary between the two logit, while the effect of the other covariates is constant.

3 Preliminary results and first conclusions

In general, the results for the two outcomes (JSF and DTF) show a high degree of similarity (Table 1). Looking at the effect of gender, the results indicate a clear disadvantage for women in entering employment. For both JSF and DTF, the estimated odds ratio of being employed in a low-skill job versus being not employed are significantly lower for women than for men (0.72 and 0.71, respectively). By contrast, there is no evidence of gender differences in the second transition. This could suggest that, in our sample, women are less likely than men to enter the labour market; however, once employed, they have similar chances of holding a job that matches their skills. As expected, having a STEM degree increases the probability of both having a job and finding a job that matches one's skills. For both outcomes, the STEM coefficients are positive and significant when we compare (2) and (1), indicating that STEM graduates are more likely to move from non-employment to low-skill employment (or low training adequacy) than non-STEM graduates (the corresponding odds are more than double). The STEM effect remains positive and significant when we compare (3) and (2). The result shows that STEM graduates still have higher chances of being in high-skill jobs rather than low-skill jobs (the corresponding odds are just below 2). Finally, when we compare (2) and (1), the interaction term between Gender and STEM is negative and significant, implying that the employment advantage associated with a STEM degree does not compensate for the female disadvantage in entering the labour market. When we compare (3) and (2), the interaction term is not statistically significant, indicating that, once employed, the combined effect of gender and STEM degree does not play any role in the likelihood of holding a skill-matched job or a skill-mismatched job. In conclusion, the analysis highlights that Italian female graduates show a disadvantage in entering the labour market within a year of graduation, and that this disadvantage persists even among female graduates in STEM fields. Conversely, women who do

find employment have the same chances as men of doing jobs that make adequate use of the skills and training acquired at university (in their perception). STEM degrees seem to improve initial employment opportunity and the likelihood of accessing highly skilled jobs for all graduates, but they do not eliminate the female disadvantage in entering the labour market.

Table 1 Results for Adjacent Category Logit models, by JSF and DTF

	JSF		DTF	
	Odds Ratios	95%CI	Odds Ratios	95%CI
(Intercept 2 vs 1)	0.05***	0.04 – 0.08	0.06***	0.04 – 0.09
(Intercept 3 vs 2)	0.05***	0.04 – 0.08	0.09***	0.07 – 0.14
Gender [Woman] (2 vs 1)	0.72***	0.65 – 0.78	0.71***	0.64 – 0.78
Gender [Woman] (3 vs 2)	0.97	0.88 – 1.07	1.02	0.92 – 1.12
STEM [Yes] (2 vs 1)	2.70***	2.38 – 3.07	2.43***	2.13 – 2.78
STEM [Yes] (3 vs 2)	1.69***	1.51 – 1.89	1.98***	1.76 – 2.22
Gender [Woman] × STEM [Yes] (2 vs 1)	0.64***	0.54 – 0.76	0.65***	0.54 – 0.78
Gender [Woman] × STEM [Yes] (3 vs 2)	1.02	0.87 – 1.19	0.96	0.81 – 1.13
N	12,018		12,018	

$^{***} = p - value < 0.001$

Controls: Degree Year (2018–2023), Graduation delay, Area of residence, Average exam grade, Work before degree.

Acknowledgements The authors acknowledge financial support under the National Recovery and Resilience Plan (NRRP), Mission 4, Component 2, Investment 1.1, Call for tender No. 104 published on 2.2.2022 by the Italian Ministry of University and Research (MUR), funded by the European Union – NextGenerationEU – Project Title "Stem in Higher Education & Women INequalitieS", CUP I53D23004810006, Grant Assignment Decree No. 1060 adopted on 07/17/2023 by MUR.

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Gender Equality and Inclusion: A Website Analysis in the Life Sciences Industry

Laura Benedan

Abstract This work aims to investigate whether Italian life sciences companies strategically communicate their commitment to gender equality through their corporate websites. The analysis, based on 55 companies, verifies if contextual factors—such as company size, financial performance, leadership gender, and the presence of inclusive workplace policies—predict the existence of a dedicated web page on gender equality and inclusivity. Logistic regression analysis revealed that the presence of a female CEO is the only significant predictor. In contrast, company size, revenue, and internal D&I policies showed no significant influence, suggesting a gap between internal action and external communication.

Key words: Gender Equality; Women in Leadership; Inclusion and Diversity; Life Sciences Sector; Websites Analysis; Survey.

1 Introduction

The life sciences industry, encompassing pharmaceuticals, biotechnology, and medical devices, is a pivotal driver of innovation and public health advancements. However, despite women constituting a considerable proportion of the workforce and often possessing higher educational qualifications, they remain underrepresented in executive leadership and corporate board positions. This gender imbalance can be attributed to a complex interplay of societal norms, organizational practices, and individual career trajectories [3]. Structural barriers, including gender biases, limited mentorship opportunities, and challenges in balancing professional and personal responsibilities, further hinder women's progression into senior leadership roles. This underrepresentation has implications for organizational performance, innovation, and decision-making. Research has demonstrated that gender-diverse leadership teams tend to exhibit enhanced effectiveness and responsiveness to market demands, thereby underscoring the imperative to address

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this imbalance [4]. Despite an increasing emphasis on gender diversity in the corporate sphere, the extent to which life sciences companies publicly communicate their commitment to gender equality remains unclear. Corporate websites serve as key communication platforms, reflecting an organization's values, priorities and strategic direction. The visibility and prominence of gender equality messaging on these websites therefore provide insights into how companies integrate diversity and inclusion into their organizational culture and operational strategies. While Environmental, Social, and Governance (ESG) principles have gained prominence in corporate policies, gender equality may not always be explicitly addressed in these frameworks. A lack of transparency in corporate communication can obscure the true extent of companies' diversity efforts and hinder external assessments of their commitment to gender inclusion. This study examined how life sciences companies presented and prioritized gender equality initiatives through their online presence. A similar research method has been applied (for example, [2]) who analyzed Australian construction company websites to assess gender equality and career development initiatives. This research was conducted by the Laura Benedan, Cinzia Colapinto, Paolo Mariani, Laura Pagani and Mariangela Zenga [1].

2 The Study

To explore these challenges, a study was conducted in collaboration with HPS-AboutPharma and the Intersectoral Group of Personnel Directors (G.I.D.P. - H.R.D.A.), focusing on gender inclusion policies in Italian life sciences companies.use. Following the Walk and Talk Theory (Schons and Steinmeier, 2016), which posits that companies may either integrate corporate social responsibility into their core strategy or merely engage in symbolic communication, we investigated whether businesses assign strategic value to diversity and inclusion (D&I) in their external communication: only 25% of the surveyed companies had a dedicated web page on gender equality. This work suggests that while some companies integrate gender equality into their mission, vision, or ESG frameworks, this is not uniformly reflected in dedicated web content.

We conducted a logistic regression analysis, evaluating the likelihood of having a dedicated web page on gender equality and inclusivity based on various independent variables. The dependent variable in our model was the presence (1) or absence (0) of such a web page. The explanatory variables included:

- Presence of a Female CEO
- Number of Employees
- Sales Revenue (in thousands of Euros)
- Number of Inclusive Workplace Policies

Table 1. Results of logistic regression (dependent variable: Web Page dedicated to gender equality and inclusivity)

Variable	β	S.E.	Wald	df	Sign.	Exp(β)
Constant	-2.941	1.009	8.496	1	0.004	0.053
Presence of a female CEO	2.390	1.042	5.256	1	0.022	10.911
Number of employees	0.001	0.002	0.081	1	0.776	1.001
Sales revenue (in 1.000 Euros)	0.002	0.002	0.958	1	0.328	1.002
Number of Inclusive Workplace Policies	0.245	0.351	0.486	1	0.486	1.277

As shown by the results reported in Table 1, the presence of a female CEO was the only significant predictor of having a gender equality web page, highlighting leadership as a key driver of transparent and proactive communication. In contrast, neither company size, financial capacity, nor the adoption of inclusive workplace policies predicted the presence of such communication. This disconnect points to a phenomenon of "silent implementation," where internal efforts are not clearly communicated externally. One possible explanation is that companies are concerned about the risk of being perceived as inauthentic or engaging in tokenistic behavior, particularly if their inclusion initiatives are still nascent or lack measurable impact. This fear of public scrutiny may lead organizations to communicate cautiously or avoid external messaging altogether. Additionally, smaller companies often lack the communication infrastructure or strategic resources necessary to highlight their internal D&I practices. In sectors like life sciences, which are traditionally focused on technical excellence and scientific innovation, there may be cultural norms that de-emphasize social responsibility in public communications. Furthermore, the absence of standardized metrics or benchmarks to evaluate the success of diversity initiatives may cause uncertainty about what to communicate and how, thus reinforcing this phenomenon of silent implementation. Together, these factors create a significant communication gap that raises concerns about corporate accountability and stakeholder trust. To ensure accountability and foster stakeholder trust, it is crucial for companies not only to implement inclusive policies but also to make them visible through coherent and strategic communication. Greater transparency would strengthen the alignment between internal values and external representation, advancing gender equality both symbolically and structurally.

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Indirect Effects of Special Economic Zones: The Territorial Context of SEZ Campania

Andrea Ciccarelli, Audrey De Dominicis, Greta Torquati and Valentino Piunti

Abstract Special Economic Zones (SEZs) have been increasingly used in Italy to reduce regional disparities and foster economic growth in the South. While prior research focuses on direct effects, evidence on indirect spillovers is limited. This study extends Bergantino et al. [2] on ZES Puglia to ZES Campania. Using firm-level data from the AIDA database (2017–2021), we examine the impact on transport and logistics firms, excluded from direct fiscal incentives. Employing a Matching Difference-in-Differences approach with Coarsened Exact Matching, our goal is to test whether there are also positive indirect effects in Campania.

Key words: SEZ, spillover, firm performance, Difference-in-Difference, Campania

1 Introduction

Special Economic Zones (SEZs) are widely used as policy tools to foster economic development in disadvantaged regions through fiscal incentives, regulatory simplifications, and improved infrastructure. Their diffusion has been particularly strong in emerging economies, but SEZs have recently gained relevance in Europe to address regional disparities. Italy represents a notable case due to the long-standing economic dualism between northern and southern regions. In response, the Italian government introduced SEZs in 2017, which became operational between 2018 and 2019. SEZ Campania was formally established on 11 May 2018 and became

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operational for fiscal incentives on 28 September 2019. Italian SEZs require at least one port connected to the Trans-European Transport Network, emphasizing transport and logistics. Fiscal incentives target most productive sectors, while transport and logistics firms are formally excluded but may be indirectly affected through increased activity and infrastructure investments. This study focuses on SEZ Campania, one of the most economically relevant SEZs in Southern Italy, hosting major ports such as Naples and Salerno. Using firm-level data from 2017–2021 and a Matching Difference-in-Differences approach, the analysis aims to assess whether firms located in SEZ municipalities experienced higher revenue after the policy's implementation compared to similar firms outside SEZ areas.

2 Brief literature review

Different studies demonstrated that tax incentives can positively impact the economic growth of countries and regions. As suggested by recent literature, policy evaluation requires a comprehensive approach [2]. For this reason, considering only direct effects can be not sufficient to fully explore the issue, as this approach can neglect indirect effects, especially on firms not directly targeted by the policy [4,5,6].

Notably, as highlighted by the existing literature, logistics has a crucial role in regional economic growth, as demonstrated by European studies [1,3]. In their research, Nisticò and Prota [7] consider the SEZs policy in Italy, highlighting its importance to foster the industrial growth of the economically lagging regions. Bergantino et al. [2] analyze the indirect effects of SEZ on the transport and logistic sectors, which are excluded from SEZ benefits.

Thereby, their contribution helps to fill the lack of impact of place-based policy literature by also considering impacts on non-directly affected areas, recognising the role of regional economic context [8[.

Following Bergantino et al., we apply a Matching Difference-in-Differences, as suggested also by Wu et al [9].

3 Data and methodology

Our study focuses on transportation and logistics companies (ATECO codes 49–52) in the Campania region over 2017–2021, using data from the AIDA Bureau Van Dijk database. The sample comprises 8,404 firms, and firm-level variables include revenue, value added, employees, and total assets. SEZ Campania was formally established in 2018, with activities starting in 2019; therefore, 2019 is considered the year of the SEZ's effective implementation.

To evaluate the impact of the SEZ policy, we apply a Matching Difference-in-Differences approach, comparing firms located within SEZs (treated) with those outside (control) across the pre- and post-implementation periods. The treatment effect is estimated through a DiD regression that incorporates control variables, as

well as firm and time fixed effects.

The DiD regression is specified as follows:

$$y_{i,p,t} = \alpha + \beta_1 Sez_i + \beta_2 Post_t + \beta_3 Sez_i \, x \, Post_t + pControls'_{i,p,t} + \varepsilon_{i,t}$$

The dependent variable *y* is the revenue of firms *i*, included in the municipality *p*, in year *t*; Post is a dummy variable indicating the period after the implementation of the policy and Sez is a dummy variable denoting if the considered firm is in a SEZ area.

4 Results

The empirical results, reported in Tables 1, 2, and 3, support the validity of the counterfactual approach adopted and provide evidence supporting the existence of indirect effects of the Campania SEZ on firms operating in the transport and logistics sector. First, the parallel trend test (Table 1) does not reveal statistically significant differences in pre-treatment trends between treated and control firms, suggesting that the parallel trends assumption is plausible in the period preceding the implementation of the policy. Second, the Difference-in-Differences estimates (Table 2), obtained on the balanced sample constructed through Coarsened Exact Matching, show a positive and statistically significant coefficient on the *SEZ* × *Post* interaction term, indicating an increase in firm revenues of approximately 4% for firms located in SEZ municipalities after 2019, conditional on firm characteristics and controlling for firm and year fixed effects. Finally, the placebo test (Table 3), based on a fictitious policy implementation date, yields no significant effects on the placebo interaction term, thereby reinforcing the causal interpretation of the main results and suggesting that the estimated effects are not driven by spurious dynamics or unobserved common shocks.

Table 1: Parallel trend test

Null hypothesis	***F-statistic***	***p-value***
H_0: Dm2 = 0	0.05	0.818

Notes: The table reports an F-test on the coefficient of the lead of the treatment indicator. Failure to reject the null hypothesis indicates no evidence of differential pre-treatment trends between treated and control units.

Table 2: DiD Regression

	(1) ln Revenues
SEZ x Post	0.040*** (0.014)
Post	-0.134*** (0.020)
Log Employment	0.528*** (0.058)
Log Assets	0.640*** (0.063)
Log Value Added per Capita	0.790** (0.250)

Notes: The coefficient on ZES × Post is the DID estimate. Standard errors clustered at the firm level are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 3: Placebo test

	ln(rev)
Post placebo (post_pl)	-0.1277425*** (0.020668)
SEZ x Post placebo	0.0261033 (0.0179711)

Note: Robust standard errors clustered at the ID level are reported in parentheses. The SEZ dummy is omitted (baseline category). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5 Preliminary remarks

Overall, the analysis provides preliminary evidence that the Campania SEZ has generated indirect positive effects on firms operating in the transport and logistics sector, despite their formal exclusion from direct fiscal incentives. These findings are consistent with previous evidence on the Apulia SEZ and support the view that SEZ policies may produce spillover effects along production and logistics chains. The results also highlight the importance of the territorial and infrastructural context, suggesting that firms' location within the SEZ area and their proximity to major transport nodes play a key role in the transmission of policy effects. Future research will aim to extend the analysis by considering alternative specifications, additional outcome variables, and further robustness checks, in order to better assess the magnitude and persistence of the estimated effects.

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Individual Economic Insecurity: A Trajectory-Based Composite Measure

Giacomo Gobber, Silvia Pacei and Paolo Verme

Abstract Economic insecurity has attracted attention in recent years, yet there is still no consensus on how to define and measure it. We propose a novel individual index of economic insecurity shaped both by individuals' past experiences and their positioning within a defined reference group. We combine two longitudinal dimensions to capture personal income dynamics and the comparison between each individual income trajectory and that of peers. An application to the German Socio-Economic Panel (SOEP) highlights that the measure is a significant determinant in models for individual perceptions of concerns about certain socio-economic phenomena.

Key words: Economic insecurity, Inter-temporal measurement, Reference groups, SOEP data

1 Introduction

Insecurity is commonly associated with the individuals' anxiety about future financial stability and their ability to cope with potential economic shocks. Its relevance is growing due to recent crises and considering its influence on many social phenomena. Indeed, significant efforts have been made to define and measure economic insecurity at individual level [2] but a universally accepted framework is still lacking. The existing measures can be classified in different ways, as they can have a

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retrospective look by using past information [2] or a future-oriented perspective [4]. Moreover, they can be classified into subjective or objective measures.

We propose a class of objective measures aimed at capturing individual's forward-looking perception of future outcomes based on past experience. In particular, we extend the inter-temporal measures suggested by Gallo et al. [5], by modifying one of the two components. The first component takes into account the individuals' economic resources fluctuations over time. For the second component, we suggest a comparison with a reference group in terms of "trajectory", assuming that individuals compare their own economic condition with relevant others in terms of resource trajectories across time. The new definition of economic insecurity we refer to can therefore be expressed as

> the anxiety produced by the possible exposure to adverse economic events and by the anticipation of the difficulty of recovering from them, combined with the anxiety associated to unfavorable comparisons of one's own economic condition with relevant others, in terms of relative resource trajectories across time.

2 The Measure

Given our novel definition of economic insecurity, we propose a class of composite indices that includes two components. The first component identifies with the class of indices of Gallo et al. [5] and captures individual income dynamics over time in relative terms by evaluating past resources fluctuations.

Consider a population of $N \in \mathbb{N}$ individuals, observed over $T+1$ points in time, $T \in \mathbb{N}$, where 0 denotes current time and $-T$ represents the furthest observed point in the past $(-T,\ldots,0)$. Each individual i $(i = 1,\ldots,N)$ has an economic resource stream given by $x_i = (x_{i,-T},\ldots,x_{i,0})$. The first part of the index is defined as a function that assigns an insecurity value to each individual:

$$LI_R^T(x_i) = l_0 \sum_{\substack{t\in\{1,\ldots,T\} \\ x_{i,-t}>x_{i,-(t-1)}}} \delta^{t-1} \ln\left(\frac{x_{i,-t}}{x_{i,-(t-1)}}\right) + g_0 \sum_{\substack{t\in\{1,\ldots,T\} \\ x_{i,-t}<x_{i,-(t-1)}}} \delta^{t-1} \ln\left(\frac{x_{i,-t}}{x_{i,-(t-1)}}\right)$$

It is a weighted sum with weights denoted by l_0 (losses) and g_0 (gains) ($l_0, g_0 \in R_{++}$). δ is an inter-temporal weight that must take a value in $(0, \min[l_0/g_0; g_0/l_0])$, as demonstrated by Bossert et al. [2], in order to give increasingly low relevance to relative changes going back in time. Moreover, g_0 must be lower than l_0 assuming that losses have greater impact than gains. This component assigns a higher level of insecurity to individuals unable to recover after experiencing a loss in resources.

For the second component, we quantify the relative change in an individual's economic resource level compared to their peer's group over time. We consider the population to be divided into $J \in N$ mutually exclusive and collectively exhaustive reference groups, each denoted by $j \in (1,\ldots,J)$ and containing N_j individuals. Each individual $i.th$, assigned to reference group $j(i)$, compares her own resource trajectory to that of her peers between a given time point in the past $-k$ and current time.

e denote median resource level of $j(i)$ at a given past time as $Me_{j(i),-k}$. We thus can define:

$$TCI(x_{j(i),0}) = \ln\left(\frac{\frac{Me_{j(i),0}}{Me_{j(i),-k}}}{\frac{x_{ij,0}}{x_{ij,-k}}}\right) = \ln\left(\frac{Me_{j(i),0}}{Me_{j(i),-k}}\right) - \ln\left(\frac{x_{ij,0}}{x_{ij,-k}}\right)$$

Its sign and magnitude provide insights into whether an individual's trajectory is improving or worsening relative to the median trend of their reference group[1].

To combine the two components we choose a weighted mean. Therefore, the proposed class of composite indices, that we call *CIdelta*, is defined as:

$$CIdelta^T(x_i^*) = \varepsilon LI_R^T(x_i) + (1-\varepsilon)TCI(x_{j(i),0})$$

where $\varepsilon \in [0,1]$ is a constant weight. ε can be determined by maximizing the correlation ratio[2]. Our index satisfies a set of desirable properties: gain-loss monotonicity, proximity monotonicity, quasi-linearity, stationarity and scale-invariance.

3 Empirical analysis

Measures are computed on German Socio-Economic Panel (SOEP) for 2011-2022, setting T=4 for the first component and k=1 for the second one[3]. As individual resource we use equivalized household disposable income, deflated with 2022 prices. Following Budría and Ferrer-i-Carbonell [3], the reference group is defined for each time t at individual level by conditioning on NUTS1 geographical regions, gender, age (5 classes) and education (3 classes). The composite inter-temporal index is obtained by setting the parameters of the first component as: $g_0 = 15/16$, $l_0 = 1$ and $\delta = 0.9$, coherently with literature [1, 5]. ε results in 0.525, computed relying on a subjective survey question related to the satisfaction with household income.

Our aim is to assess whether our proposed index improves the measurement of perceived economic insecurity with respect to the mentioned Gallo et al. [5] measure (*CI*). To this purpose, we study the relationship between economic insecurity, considered as a determinant, and a set of ordinal variables capturing subjective individual evaluations in different domains as, for instance, in Watson et al. [6].

We estimate random-effects ordered probit models with controls for outcomes related to personal concerns: worried about economic development, worried about environment and worried about crime. Moreover, we consider the level of personal interest for politics and the party preference intensity. We include in the models in

[1] Note the twofold interpretation: "worsened" means either that individual has *declined more* or *grown less* than the reference group. Conversely, "improved" refers to the individual that has either *increased more* or *declined less* than the group.

[2] The correlation between the dispersion of the individual scores derived from the composite index within the categories defined by a subjective question about individuals' perception of their economic conditions, and the total score dispersion.

[3] To capture, for instance, the individuals' income rebound in the first post-pandemic year relative to the median rebound of her peers, thus comparing the ability to react to an economic shock.

turn either *CIdelta* or *CI* as a determinant. Results show that *CIdelta* is statistically significant in all specifications and consistently associated with higher level of worries, while *CI* is not significant in the "worried about economic development" model (Table 1). Both *CI* and *CIdelta* have negative effect on the levels of interest for politics and party preference intensity. Models with *CIdelta* perform better in terms of AIC and BIC than those including *CI*, except for the "worried about environment" case. Findings suggest that our measure adds meaningful information about how individuals experience and assess their economic insecurity. The proposed measure provides a tool for researchers and policymakers interested in monitoring this growing phenomenon and in quantifying its connections across subjective outcomes of various natures.

Table 1 Regression results – Worried about economic development

	Coeff.(Std. err.)	**Coeff.(Std. err.)**
CIdelta	0.0348^{**}	–
	(0.0145)	
CI	–	0.0015
		(0.0182)
Log(eq. household income)	0.1160^{***}	0.1023^{***}
	(0.0117)	(0.0146)
N. children	0.0241^{***}	0.0256^{***}
	(0.0065)	(0.0066)
18–30 years old	0.2539^{***}	0.2549^{***}
	(0.0256)	(0.0256)
31–40 years old	0.0601^{***}	0.0600^{***}
	(0.0214)	(0.0214)
41–50 years old	-0.0210	-0.0198
	(0.0190)	(0.0190)
51–60 years old	-0.0590^{***}	-0.0573^{***}
	(0.0160)	(0.0162)
High school	-0.2287^{***}	-0.2319^{***}
	(0.0147)	(0.0149)
Less than high school	-0.1860^{***}	-0.1920^{***}
	(0.0220)	(0.0225)
Male	0.1757^{***}	0.1761^{***}
	(0.0129)	(0.0129)
Divorced	-0.1176^{***}	-0.1205^{***}
	(0.0264)	(0.0264)
Married	-0.1359^{***}	-0.1330^{***}
	(0.0191)	(0.0191)
Separated	-0.1631^{***}	-0.1639^{***}
	(0.0360)	(0.0360)
Widowed	0.0155	0.0122
	(0.0319)	(0.0320)
Employed	-0.0106	-0.0102
	(0.0124)	(0.0124)
East Germany	0.0150	0.0123
	(0.0180)	(0.0181)
North Germany	0.1179^{***}	0.1175^{***}
	(0.0198)	(0.0198)
South Germany	0.0840^{***}	0.0847^{***}
	(0.0163)	(0.0163)
Observations	183,273	183,273
AIC	296750.2	296756.5
BIC	297063.9	297070.2

Notes: Our elaborations on SOEP. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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Innovative systems of environmental and ecosystem services accounting: opportunities, challenges and implications for European Union policies

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Abstract Integrating environmental accounting and ecosystem services into economic modelling is a key challenge for the ecological transition. Recent developments in the System of Environmental Economic Accounting (SEEA), reinforced at the European level by Regulation (EU) 2024/3024, introduce new tools to better measure ecosystems, ecosystem services, and natural capital. This paper explores how environmentally extended input-output models can support these advances and EU environmental policies, outlining methodological progress, policy uses, and remaining challenges in linking economic activities with ecosystem services and sustainability goals within a coherent framework.

Keywords: Environmental accounting, Ecosystem services, Input-output models, SEEA, European environmental policies

1 Introduction

The growing interdependence between economic and natural systems has increasingly highlighted the inadequacy of traditional economic indicators in representing the true conditions of sustainable development. In this context, environmental accounting has progressively established itself as a fundamental tool for integrating economic and environmental dimensions into a coherent statistical framework. At the international level, the System of Environmental Economic Accounting (SEEA), developed by the United Nations, represents the methodological reference for integrating economic and environmental accounting

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[7, 8]. At the European level, Regulation (EU) 691/2011 translated this framework into a harmonized system of environmental accounting based on common statistical requirements. The adoption of Regulation (EU) 2024/3024 marks a further fundamental step, extending the scope of European environmental accounts through the introduction of new modules dedicated to ecosystems, ecosystem services, and natural capital. These innovations also pose new challenges and opportunities for economic modeling, particularly for input-output models, traditionally used to analyze sectoral interrelationships and the environmental impacts of economic activities. The international scientific literature has extensively developed these approaches, highlighting how environmentally extended input–output (EEIO) models are effective tools for analyzing environmental footprints, emissions embedded in international trade, and the indirect effects of climate policies [5, 6]. More recent studies have applied multi-regional models to estimate carbon and resource-use footprints at national and sectoral levels, demonstrating their usefulness for assessing transition scenarios and monitoring climate and energy targets. However, the integration of ecosystem services into these models remains an evolving field, particularly in the European context.

2 The framework of environmental economic accounting in the EU

European environmental economic accounting integrates official statistics, economic analysis, and public policies by providing structured and comparable information on environmental pressures, natural resource use, and economic system responses. Regulation (EU) 691/2011 introduced the first mandatory environmental accounting modules, including air emissions accounts, environmental tax accounts, and material flow accounts [4]. Although these tools significantly improved the information base for environmental policies, they still failed to capture the relationships between the economy, the environment, and ecosystems. Regulation (EU) 2024/3024 expanded this framework, introducing new modules relating to the accounting of ecosystems and ecosystem services [2]. The aim is to bridge the information gap between economic accounting and the ecological dimension, enabling a more comprehensive assessment of the effects of European policies in areas such as biodiversity, land use, agriculture, and climate change. Ecosystem accounting is based on the identification of ecosystem units, the measurement of their extent and condition, and the assessment of ecosystem service flows. A central element of the new approach is the use of a harmonized information base, built largely from Earth observation data and official statistical sources. In particular, the use of satellite data allows for a coherent and comparable mapping of ecosystems, their conservation status, and the dynamics of change over time, overcoming many of the limitations associated with the fragmentation of sources and methodological differences between Member States [3]. The standardization proposed by SEEA Ecosystem Accounting allows for the integration of this information into economic accounts, creating the conditions for a systematic analysis of the interactions between productive sectors and natural capital.

3 Input-output models and environmental accounting

Input-output models are one of the most well-established tools for the structural analysis of economic systems. Their extension with environmental variables allows us to overcome a limited sectoral perspective and consider impacts along the entire value chain [1]. In Environmentally Extended Input-Output Models (EEIO), traditional economic matrices are complemented by information on emissions, resource consumption, and environmental pressures. This approach allows us to assess not only the direct environmental impacts of production activities but also the indirect impacts arising from the links between different economic sectors, considering both the goods and services used in production processes and those intended for final consumption, investment, and exports. The integration of the environmental accounting modules required by Regulation (EU) 2024/3024 offers the opportunity to include ecosystem services in EEIO models, significantly expanding their analytical potential. The inclusion of ecosystem services in input-output models poses significant methodological challenges related to the representation of non-market flows, the choice of measurement units, and monetary valuation. However, advances in ecosystem accounting allow these services to be treated as key inputs for certain economic sectors, particularly agriculture, forestry, tourism, and land management. This integration allows for a more comprehensive analysis of the trade-offs between economic growth and ecosystem conservation, providing useful insights for policies geared towards long-term sustainability. Simulations based on European environmental accounting data show that reducing final demand in land-intensive sectors can trigger amplified indirect effects along supply chains, resulting in land-use reductions greater than the initial cut. Likewise, integrating climate regulation services into EEIO models reveals that ecosystem restoration can generate broad benefits across interconnected sectors.

4 Implications for EU environmental policies

The integration of input-output models with advanced environmental economic accounting strengthens the connection between official statistics and policymaking, fostering closer alignment between economic analysis and environmental objectives. At the European level, these tools support major strategic frameworks such as the Green Deal and the EU Biodiversity Strategy for 2030 by providing a solid quantitative basis to assess policy impacts on climate neutrality, biodiversity, and the sustainable use of natural resources. Environmentally Extended Input-Output (EEIO) models enable the simulation of alternative policy scenarios and the evaluation of both direct and indirect effects along value chains. The incorporation of ecosystem accounting further enhances their relevance, particularly for the implementation of Regulation (EU) 2024/1991 on nature restoration, as it allows restoration measures to be linked to economic impacts and ecosystem service benefits. Overall, this integrated approach supports a systemic assessment of environmental policies, improves coherence among economic, environmental, and social goals, and strengthens evidence-based decision-making processes.

5 Conclusions

This paper highlights how recent developments in European environmental economic accounting, and in particular Regulation (EU) 2024/3024, open new perspectives for analyzing the interactions between the economy and the environment, strengthening the role of official statistics as a tool to support public decision-making. Extending economic accounting to ecosystems and ecosystem services allows us to overcome a partial view of the relationships between economic activities and the environment, making the contribution of natural capital to the functioning of the production system and collective well-being more explicit. The integration of environmental accounting and EEIO models is applied in environmental footprint analyses and scenario assessments at the European level. Strengthening these applications, also considering the new modules introduced by Regulation (EU) 2024/3024, can support a more systematic and comparable evaluation of the impacts of EU environmental policies. Within this framework, environmentally extended input-output models emerge as fundamental tools for integrating ecosystem services into economic analysis, as they allow us to connect economic flows to physical and environmental flows along the entire production chain. These models capture both direct and indirect environmental impacts across sectors and final consumption, providing a robust quantitative basis for evaluating environmental policies. Strengthening the link between environmental accounting and economic modeling is therefore essential for addressing the ecological transition in an informed and systemic manner. In a global context characterized by growing pressure on natural resources and increasingly ambitious climate and environmental objectives, the availability of integrated analytical tools is crucial for guiding public policies toward more sustainable, coherent, and evidence-based development paths.

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Integrating Tourism Pressure into the Municipal Fragility Index: Evidence from the Aosta Valley

Laura Marcis and Consuelo Rubina Nava

Abstract The fragility of mountain areas has become a key issue within environmental policy, especially in light of the recent revision of mountain legislation, which highlights the need for targeted and long-term interventions to address their structural vulnerabilities. To this aim, the composite fragility index based on twelve elementary indicators developed by ISTAT summarizes socio-economic and demographic dimensions of fragility. However, further sources of territorial pressure may exacerbate existing fragility. Accordingly, by incorporating tourism intensity relative to local accommodation capacity, a novel fragility index is calculated for municipalities in the Aosta Valley. The enhanced index better identifies municipalities where tourism pressure amplifies structural fragility, thereby highlighting areas that warrant increased policy attention.

Key words: municipal fragility index (MFI) , AMPI+, Aosta Valley, tourism

1 Introduction

Mountain areas represent some of the most complex and vulnerable territorial contexts in Italy and across Europe. While these regions are characterized by an exceptionally rich natural, landscape, and cultural heritage, they are simultaneously exposed to a wide range of criticalities that challenge their environmental, economic, and social sustainability. The development of the Municipal Fragility Index (MFI) [2] by the Italian National Institute of Statistics (ISTAT) accomodates the idea that the vulnerability of a territory is the result of a complex interplay among

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environmental, demographic, economic, and infrastructural conditions. In mountain municipalities, where the balance between humans and the environment is particularly delicate, fragility takes on a systemic dimension: progressive depopulation, population aging, difficulties in maintaining essential services, and dependence on a limited number of productive sectors all contribute to reducing the overall resilience of the territory. The MFI provides a synthetic measure of the level of fragility of municipalities to identify areas most exposed to specific risk factors and facilitate the territorial analysis of the phenomenon over time. The index is constructed through the combination of twelve elementary indicators that describe the main territorial, environmental, and socio-economic dimensions of municipal fragility. The methodology used for the transformation and aggregation of the elementary indicators is based on the assumption of non-substitutability among the different components; therefore, the MFI is a non-compensatory composite index (or partially non-compensatory, Adjusted Mazziotta-Pareto Index, AMPI+) [1]. Under the assumption of non-substitutability or partial substitutability of the elementary indicators, the compensatory effect of the arithmetic mean is corrected by adding a factor that depends on the variability of the indicators for each municipality with respect to the reference values used for normalization. This methodology assigns each municipality an index value that is comparable both over time (2018, 2019, and 2021) and across territories, using the national value for Italy in 2018, set equal to 100, as the reference parameter. However, further sources of territorial pressure may exacerbate existing fragility. Therefore, this paper aims at introducing, in addition to the twelve indicators proposed by ISTAT, a thirteenth indicator. Hereafter, referred to as PRatio (Pressure Ratio) is designed to capture the intensity of tourist flows and local infrastructural capacity, highlighting how a given volume of tourists may generate very different impacts in municipalities with distinct structural characteristics. In particular, a high PRatio value indicates elevated tourism pressure relative to accommodation capacity, suggesting a potential risk of overload and territorial fragility. The analysis subsequently compares the index based on the original twelve indicators - recalculated using the Aosta Valley as the reference region rather than Italy as a whole - with the index that also incorporates the thirteenth indicator. This territory is of particular interest, as it is entirely composed of mountain municipalities even under the new mountain legislation and is characterized by a strong tourism vocation. The comparison of the two index versions enables the identification of municipalities where tourism pressure constitutes a critical driver of vulnerability.

2 Method and application

Considering the accommodation capacity of each municipality, the PRatio is defined as $\text{PRatio} = \frac{T_i}{P_i}$ where T_i is the average number of tourists in the municipality i, calculated by dividing the annual number of tourist overnight stays by 365; and P_i is the equivalent population: it measures the total number of people physically present in a municipality, combining legal residents, with temporary visitors. The latter is

obtained taking into account the occupancy rate, $p = \frac{On_i}{B \times 365} * 100$, where On_i are the overnight stays in each municipality. The PRatio is then combined with the other twelve indicators ($j = 1, \ldots, 12$) used by ISTAT for the MFI. To obtain the MFI, the AMPI+ method normalizes the twelve indicators - collected in the matrix $\mathbf{X} = \{x_{ij}\}$ - according to the following formula:

$$r_{ij} = \frac{x_{ij} - Min_{x_j}}{Max_{x_j} - Min_{x_j}} * 60 + 70$$

where r_{ij} and x_{ij} are, respectively, the normalized value and the value of indicator j in municipality i. $Min_{x_j} = Ref_{x_j} - \Delta$ and $Max_{x_j} = Ref_{x_j} + \Delta$ are goalposts defined so as to set the regional value in the year 2018 equal to 100. Ref_{x_j} is the reference value for indicator j, given by the value of the indicator for Aosta Valley in 2018; $\Delta = \frac{Sup_{x_j} - Inf_{x_j}}{2}$, and Inf_{x_j} and Sup_{x_j} are, respectively, the minimum and the maximum values of indicator j in the municipal distribution across all periods considered. The resulting values fall approximately within the range $(70; 130)$, where 100 represents the reference value (regional average in 2018). The composite index is then obtained by aggregating the normalized indicators with equal weights using the simple arithmetic mean. The synthetic index of the i-th unit is subsequently obtained by applying, with a positive penalty, the corrected version of the penalty method based on the coefficient of variation (AMPI+):

$$\text{AMPI+} = M_{r_i} + S_{r_i} \times cv_i, \quad \text{with} \quad cv_i = \frac{S_{r_i}}{M_{r_i}}$$

where M_{r_i}, S_{r_i} and cv_i are the mean, the standard deviation and the coefficient of variation of the normalized indicators value, respectively.

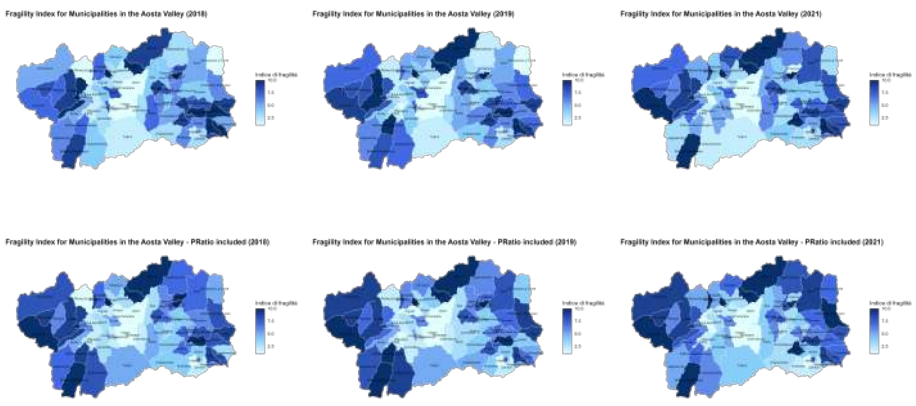

Fig. 1: Aosta Valley MFI calculated using indicators adopted by ISTAT (1^{st} row) and including the PRatio indicator (2^{nd} row). Areas with darker shades indicate higher levels of fragility. Results refers to the years 2018, 2019, and 2021.

Fig. 1 (1^{st} row) presents the MFI for each municipality, computed using the twelve indicators, while Fig. 1 (2^{nd} row) shows the MFI calculated with the inclusion of the PRatio indicator. Fig. 2 illustrates the difference between the MFI calculated with thirteen (Fig. 1, 2^{nd} row) and twelve indicators (Fig. 1, 1^{st} row). It is worth noting that, incorporating tourism pressure into the fragility index allows for the identification of territorial contexts in which tourism acts as a mitigating factor (shades of green) versus those in which it constitutes a source of increased vulnerability (shade of red), thereby providing an informative tool for the design of sustainable and differentiated territorial management policies.

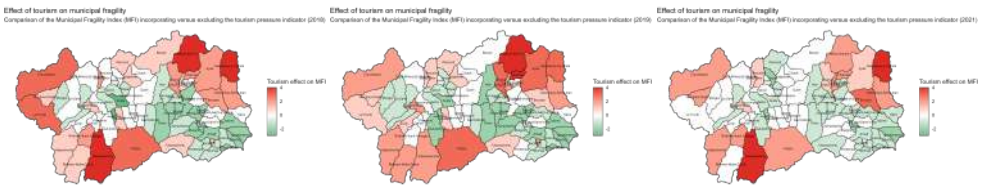

Fig. 2: Difference between the MFI based on 13 indicators (including PRatio) and on 12 indicators - years 2018, 2019, 2021. Shades of red indicate municipalities with increased fragility when tourism is included while shades of green suggest where fragility is mitigated by the additional indicator.

Acknowledgements Funded by the European Union – NextGenerationEU, Mission 4 Component 1.5 – ECS00000036 – CUP B63B22000010001 and by the project "SMARTDECO - Energia e Turismo in Aree Montane Fragili: Strategie e metodologie per il Decoupling", CUP B59J25000540007.

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Labour Market Integration, Digital Work, and Psychological Well-Being in Later Careers

Camila Cid, Ida D'Attoma and Livia Ortensi

Abstract
The labour market is undergoing a transformation driven by new technologies, with important implications for older workers. In Italy, this process is particularly relevant given the ageing workforce. Using data from the 2021 European Working Conditions Survey (EWCS), this study examines the association between labour market integration and psychological well-being among workers aged 50 and over, measured through composite indices. Results from multivariate and quantile regression models show that higher perceived labour market integration is positively associated with psychological well-being, after controlling for job insecurity, exposure to digital technologies. These findings support the need for more inclusive and sustainable work environments for older workers.

Key words: labour market integration, psychological well-being, older workers, job insecurity

1 Introduction

Population ageing and transformations in work organisation are reshaping labour markets across Europe. The diffusion of digital technologies and automation is altering how tasks are performed and the conditions under which work takes place, raising important questions about labour market inclusiveness and sustainability. Italy represents a relevant case, as it has one of the oldest workforces in Europe and an increasing share of older workers in employment. While existing research has

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extensively examined the effects of technological change on employment and wages [1], less attention has been paid to the subjective dimension of work in later working life. In this context, the present study aims to examine the association between labour market integration and psychological well-being among workers aged 50 and over in Italy, using data from the 2021 European Working Conditions Survey (EWCS).

2 Theoretical Framework

As part of the Fourth Industrial Revolution, digital technologies and automation are reshaping work tasks and conditions [7]. According to the Skill-Biased Technical Change framework [8], technological progress tends to favour highly skilled workers while disadvantaging lower-skilled ones through the automation of routine tasks, thereby increasing labour market inequality. Related approaches, such as Routine-Biased Technological Change [2], emphasise the displacement of routine tasks and the resulting job and wage polarization. Beyond employment and wages, technological change also affects job quality and workers' subjective experiences, including well-being [7].

These dynamics are particularly relevant for older workers, who may face additional barriers to adapting to technological change due to age-based stereotypes regarding adaptability, training costs, and health [5]. However, evidence shows that workers over 50 are often as productive as younger workers and may have a comparative advantage in non-routine tasks requiring experience and accumulated knowledge [1]. In Italy, where population ageing and labour market polarization are especially pronounced [4], the implications of technological change for older workers' labour market integration and psychological well-being remain underexplored, underscoring the relevance of this study. This gap underscores the relevance of examining labour market integration as a key determinant of well-being in later stages of working life [4].

3 Methodology

This study examines the association between labour market integration (LMI) and psychological well-being among workers aged 50 and over in Italy, in the context of ongoing technological change. The analysis is based on data from the European Working Conditions Survey (EWCS) 2021.

The empirical focus is on Italian workers aged 50 years and older, resulting in a final sample of 1,213 observations. Psychological well-being is measured using the WHO-5 index, a validated and widely used measure of subjective well-being [6]. Labour market integration is operationalised through a composite index based on EWCS items capturing perceived recognition, fairness, career prospects, and

opportunities to use skills at work, commonly employed indicators in job quality and working conditions research [3].

First, a single survey-weighted multivariate regression model was estimated with psychological well-being as the outcome variable, using calibrated sampling weights to ensure national representativeness and controlling for perceived job insecurity (measured as self-reported fear of job loss), exposure to digital technologies, and key sociodemographic and employment characteristics. To assess potential heterogeneity in this association across the distribution of well-being, the analysis further applies quantile regression at selected lower, median, and upper quantiles of the psychological well-being index. While the mean-based model captures average effects, quantile regression allows the relationship between labour market integration and well-being to vary across different points of the outcome distribution, which is particularly relevant given that the determinants of well-being may differ across levels of psychological well-being. All models include the same set of control variables and are estimated using survey weights to account for the complex sampling design of the EWCS.

4 Results

The results of the multivariate regression indicate that labour market integration is strongly and positively associated with the psychological well-being of older workers. High levels of digital technology use at work are also positively related to well-being, whereas the perceived threat of job loss is not statistically significant. Women report lower levels of psychological well-being than men (Table 1). Quantile regression results reveal substantial heterogeneity: the effect is stronger than the average in the middle quantiles, while it weakens and becomes negative at the upper tail of the distribution, suggesting diminishing marginal returns of labour market integration for individuals with higher levels of well-being (Figure 1). Perceived job insecurity remains non-significant throughout the distribution.

Table 1: Survey-weighted regression results for psychological well-being index

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	35.214	11.112	3.169	0.002 **
Labour market integration index	5.656	0.912	6.201	< 0.001 ***
Digital technology use (High)	3.752	1.823	2.059	0.040 *
Female (ref. Male)	−3.727	1.458	−2.557	0.011 *

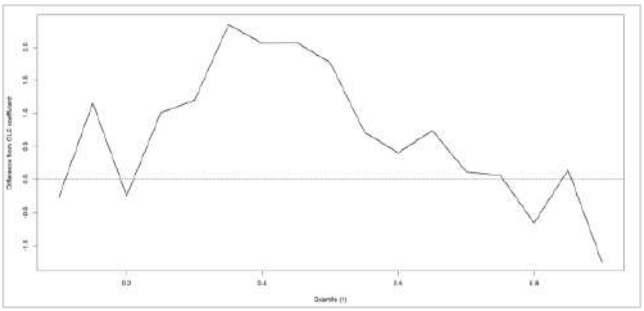
* p < .05; ** p < .01; *** p < .001. Non-significant parameters omitted for readability reasons.

5 Conclusion

The results indicate that the dimensions of labour market integration most strongly associated with psychological well-being are those related to material security and

future prospects, while more symbolic dimensions—such as recognition or opportunities to use skills—show weaker, though still significant, associations. This suggests that concrete and tangible forms of workplace recognition play a particularly important role in supporting older workers' well-being in a context of rapid digitalisation.

Figure 1: Differences in Quantile and OLS Estimates of LMI Effects on Well-being



The absence of a significant effect of perceived job loss threat may reflect heterogeneity by type of employment contract, as its implications for well-being are likely to differ between permanent and non-standard workers; future research should explore these differences explicitly.

Overall, these findings highlight actionable dimensions of labour market integration that can inform policies and organisational practices aimed at promoting more inclusive and sustainable working conditions for older workers, although results should be interpreted with caution given the broad measurement of digital technology use and the COVID-19 context of data collection.

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Local Ingredients and consumers preferences in the Beer Market: Evidence from an Italian Conjoint Analysis

Raffaele Angelone

Abstract This paper investigates consumers' preferences for local ingredients in beer production, focusing on the role of locally sourced hops and malt in shaping purchasing decisions. While existing literature extensively examines the value of local origin and craft production, limited attention has been paid to the specific contribution of local inputs, particularly within mass-produced beers. Using original survey data collected in Italy (n = 1,021), the study applies a conjoint analysis to estimate individual-level part-worth utilities associated with key product attributes. These utilities are then used to identify heterogeneous preference structures and to construct consumer personas based on revealed choice patterns rather than socio-demographic characteristics alone. Results show that local ingredients significantly enhance perceived value, especially among sustainability-oriented consumers. The findings highlight the relevance of individual utility-based segmentation for understanding preference heterogeneity and provide evidence that local sourcing represents a strategic lever for both craft and industrial beer producers.

Key words local origin, beer consumption, conjoint analysis, willingness to pay, sustainability

1 Introduction

Consumer demand for food and beverages has progressively shifted toward products that convey authenticity, quality, and local identity. Within this context, local origin functions as a powerful extrinsic cue capable of reducing information asymmetries and enhancing perceived value. While previous studies have extensively explored the role of origin in food markets, limited attention has been devoted to the specific contribution of locally sourced ingredients, particularly in mass-produced beer. This

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paper addresses this gap by investigating how consumers value the use of local hops and malt and whether these attributes influence purchasing decisions differently across consumer segments. Existing research highlights the importance of extrinsic cues—such as origin, labeling, and branding—in shaping food choices. In the beer sector, studies have primarily focused on craft production and local identity, showing that consumers are willing to pay a premium for locally brewed products. However, empirical evidence on the role of local ingredients, as distinct from local production, remains scarce. This study contributes to the literature by isolating the effect of ingredient origin and examining its relevance for both craft and industrial beers. This work is the results of a joint research effort by a group including R. Angelone, A. Ciccarelli, C. Garavaglia, P. Mariani, C. Sartirana.

2 Data and Methodology

The empirical analysis is based on a structured online survey conducted in Italy in July 2024 by Demoskopea on a sample of 1,021 respondents, designed to be representative of the adult population residing in the regions of Puglia, Emilia Romagna, and Piedmont, areas considered strategic for their geographical and socio-economic diversity. Data collection was carried out using a Computer-Assisted Web Interviewing (CAWI) methodology. The questionnaire gathered information on socio-demographic characteristics, beer consumption habits, attitudes toward sustainability, and preferences regarding beer attributes, with particular attention to ingredient origin. To investigate consumer preferences, a conjoint analysis approach was adopted. This method allows the estimation of the relative importance of product attributes by observing respondents' evaluations of alternative product profiles. In line with standard practice, beer profiles were defined through a combination of three key attributes: origin of hops (Italian vs. international), origin of malt (Italian vs. international), and price level. Different price levels were specified for industrial and craft beers to reflect realistic market conditions.

Respondents were asked to rank a set of hypothetical beer profiles generated through an orthogonal experimental design, which reduced the full factorial combination of attributes to a manageable number while preserving statistical efficiency. Rankings were then used to estimate part-worth utilities for each attribute level using an ordinary least squares (OLS) regression approach, which provides reliable estimates in conjoint settings with ranking data. To explore heterogeneity in preferences, individual-level utility estimates were subsequently employed in a cluster analysis. A k-means algorithm was applied to identify groups of consumers sharing similar preference structures. The number of clusters was determined based on interpretability and stability of results. This segmentation approach allows for the identification of distinct consumer profiles grounded in revealed preference patterns rather than purely socio-demographic characteristics. Overall, this methodological framework enables a detailed assessment of how different consumer segments value local ingredients and price attributes, providing a robust basis for interpreting preference heterogeneity in the beer market.

3 Remarks and conclusions

Results show that the origin of hops is the most influential attribute, especially among consumers sensitive to sustainability issues. Italian hops generate a positive utility across all segments, while the effect of Italian malt varies according to consumer typology. Price remains an important factor, but its relative importance decreases among consumers with stronger environmental and quality orientations.

Cluster analysis identifies four distinct consumer profiles, highlighting differentiated patterns of valuation and providing insights into market segmentation strategies. **Curious Youngster (23%)** shows a strong preference for beers made with local ingredients and high sensitivity to sustainability issues, valuing quality and ethical coherence over price. **The Price-oriented Pragmatist (30%)** is mainly driven by price considerations and shows limited interest in origin or sustainability attributes, favouring standardized industrial products. **The Premium Explorer (24%)** exhibits a strong orientation toward quality, authenticity, and local sourcing, with a high willingness to pay for craft beers and products with a clear identity. Finally, **The Curious Competent (23%)** segment displays informed but selective preferences, combining moderate price sensitivity with openness to quality cues and expert recommendations.

Overall, the segmentation highlights how individual-level utilities provide a nuanced understanding of consumer heterogeneity. By grounding market segmentation in revealed preference structures rather than demographic characteristics alone, the analysis offers a robust framework for interpreting how different consumers value local ingredients and for designing targeted marketing and product strategies. The findings confirm that local ingredients represent a significant source of value in beer market, extending beyond the craft segment to include industrial products. Emphasizing the local origin of inputs can enhance perceived quality and strengthen brand positioning. From a managerial perspective, these results support the strategic use of local sourcing and communication as tools for differentiation in increasingly competitive beer markets.

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Local Policy Evaluation at Scale: Leveraging Survey and Administrative Data

Silvia Scarpa, Massimo Baldini, Andrea Barigazzi, Giovanni Gallo and Marcello Morciano

Abstract Policymakers increasingly demand fine-grained territorial analysis, yet survey data lack geographic detail while administrative data lack socio-economic richness. We address this dilemma through spatial microsimulation, systematically comparing deterministic and probabilistic reweighting methods to align survey weights with known population benchmarks. We construct a spatially disaggregated synthetic population for municipalities in Emilia-Romagna from the Italian EU-SILC data. Our comparative analysis highlights trade-offs between computational efficiency of deterministic methods and precision of probabilistic approaches. We demonstrate methods drawbacks and advantages to guide researchers for policy evaluation at territorial level.

Key words: Spatial microsimulation, Policy evaluation, Reweighting methods

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1 Introduction

Policymakers and researchers increasingly aim to evaluate the impact of policies at the territorial level, specifically where survey and administrative data alone are insufficient to provide a complete framework. The former do not provide adequate territorial statistical representation, due to budget and time constraints; the latter cover the whole population but lack rich socio-economic variables. Spatial microsimulation (SM) methods offer a valid strategy to integrate these two sources to construct a synthetic population at the most detailed level of aggregation for which *benchmarks* are known from administrative and census data [1]. SM methods insert a spatial dimension into the microsimulation practice of evaluating policy interventions. This work offers a systematic comparison of different SM techniques, ranging from deterministic reweighting methods, namely Iterative Proportional Fitting (IPF) and the Generalized Regression Estimator (GREG), to a probabilistic approach, specifically Simulated Annealing (SA). As an illustrative case study, we employ these methods to generate a synthetic population for the residents of Emilia-Romagna municipalities, utilizing EU-SILC survey data.

2 Reweighting methods in spatial microsimulation

Reweighting methods in the SM literature aim to align the survey data S with known benchmarks X (in the form of counts) at the small area level. Deterministic procedures iteratively adjust the initial sampling weights to match these benchmarks until convergence is reached. The resulting weight may be a floating-point number, which thus requires rounding to replicate each survey individual a number of times equal to its new representativeness at the small area level. Probabilistic reweighting methods are based on sampling individuals from the survey data according to their agreement with the available benchmarks. Specifically, IPF updates each weight $w_j, j \in S$ by iteratively adjusting for each constraint $X_{d,p}$, $p = 1,\ldots,P$, independently for each area d, $d = 1\ldots,D$ [2, 4]. At step t, for individual j with characteristic $x_{j,p}$, the updated weights are computed as

$$w_{j,d}^{(t,p)} = w_{j,d}^{(t,p-1)} \frac{X_{d,p}}{\sum_{j\in S} w_{j,d}^{(t,p-1)} x_{j,p}}, \quad \forall j \in S,$$

GREG, as explained by [3], seeks to minimize a distance function (e.g., truncated chi-squared) between w_j and the new set of weights, by minimizing a Lagrangian function. Finally, Simulated Annealing (SA) is a combinatorial optimization method based on a greedy algorithm: it sets an initial temperature (typically high), swaps individuals in and out (one or more at a time), evaluates each combination according to a fitness measure, and then cools the temperature by a scale factor until it approaches zero or the error is minimized according to benchmarks [5]. This work evaluates each method using the Percentage Standardised Absolute Error, defined

as

$$PSAE_d = \frac{1}{N_d} \sum_{p \in P} | \sum_{j \in S} w_{j,d}^{(t,p)} x_{j,p} - X_{d,p} | \times 100,$$

where N_d is the population size of area d.

3 Results from municipality level reconstruction

The 330 municipalities of Emilia-Romagna are heterogeneous in size, ranging from fewer than 100 to approximately 400,000 inhabitants, and characteristics, including mountain areas, towns, and cities. This work employs a selection of benchmarks such as age classes, gender, occupation status, and household size common to all municipalities and attempts to maximize the length of the X vector using a greedy algorithm. The 2022 EU-SILC dataset consists of 2,937 observations for the region and was recoded to allow for the implementation of SM methods.

Table 1 Summary statistics of PSAE by deterministic reweighting method

Method	Mean	Std. Dev.	Min	Max
GREG	1.809	4.507	0.020	56.780
IPF	3.305	7.754	0.010	101.410

As shown in Table 1, IPF displays a higher mean PSAE and substantially larger dispersion compared to GREG, suggesting lower efficiency in matching small area constraints.

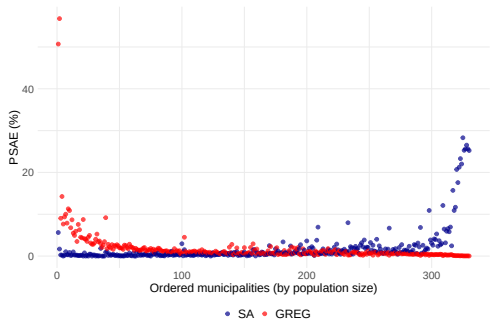

Fig. 1 Comparison of PSAE values between SA and GREG estimates across municipalities, ordered by population size.

Figure 1 shows the PSAE values ordered by municipality size for GREG and SA. It is interesting to note how the two methods complement each other: SA outperforms GREG in the smallest areas, where the integerisation bias (rounding of fractional weights) is most severe; GREG, on the other hand, performs best in medium

and large areas, where SA becomes computationally prohibitive. These results suggest a hybrid strategy.

4 Conclusion

Our synthetic populations allow us to evaluate policies and monitor phenomena such as poverty and inequality. This work demonstrates that spatial microsimulation, through reweighting techniques, allows for the reconstruction of local populations even in data-scarce contexts. A hybrid strategy that applies SA to small municipalities (e.g., rural areas) and GREG to larger ones offers an optimal balance between precision and computational feasibility. In our study, for example, we were able to estimate the Gini index in Italian municipalities, analyse its decomposition among labour categories, and use the synthetic population to study regional policies. This work demonstrated how the quality of the synthetic population is strictly conditional on the choice of benchmarks and on a rich survey data to mitigate the zero-cell problem [6]. Researchers should retain flexibility to define benchmarks ex ante based on the specific indicators they intend to evaluate.

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Local spatio-temporal Bayesian estimation of key agricultural economic indicators

Felicetta Carillo, Paolo Maranzano, Laura Marcis, Maria Chiara Pagliarella and Renato Salvatore

Abstract A Bayesian spatio-temporal extension of the Fay-Herriot small area estimation model is presented, integrating temporal dynamics via evolving random coefficients and spatial dependence through a distance-based structure. The model improves estimate reliability by borrowing strength across areas and time, capturing both overall trends and yearly increments. Its effectiveness is demonstrated using agricultural economic data characterized by spatial and temporal correlations.

Key words: agricultural economic indicators, hierarchical model, small area estimation, bayesian estimation

1 Introduction

Small Area Estimation (SAE) [3] aims at producing reliable estimates for domains or geographical areas where direct survey estimators suffer from high sampling variability due to small sample sizes. In such settings, direct estimates are often unstable and may lead to misleading inference, motivating the use of model-based approaches that borrow strength from auxiliary information and related areas. At the

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area level, the Fay-Herriot model represents the standard reference framework for SAE. This model combines direct estimators with area-level covariates through a mixed-effects specification and treats the sampling error variances as known quantities, typically obtained from design-based variance estimates of the direct estimators [2]. Consequently, inference does not focus on estimating the sampling error variances, which are assumed to be given, but rather on the latent random effects capturing unobserved area-specific heterogeneity. Building on this framework, this paper considers a Bayesian spatio-temporal small area model that extends the classical Fay-Herriot approach by incorporating both temporal and spatial dependence in the model. Temporal dynamics are captured through a random coefficients model evolving, while spatial dependence across areas is modelled using a distance-based structure. This model also allows for observing the overall evolution of the estimates and the variable yearly increments thereof [1]. The proposed methodology is illustrated through an empirical application based on data from the Farm Accountancy Data Network (FADN), a harmonized survey providing detailed economic information on agricultural holdings. The FADN collects a wide range of economic, structural, and financial variables describing agricultural activity, including production values, costs, inputs, and farm characteristics. The availability of repeated observations over multiple years and across small geographical units makes these data particularly suitable for small area estimation, especially in contexts where direct estimates at the area level are unreliable. Key economic variable such as the standard output, together with surface area variables, labor input, and livestock units, provides a measure of the performance of agricultural activity. Given the presence of both spatial proximity and temporal persistence in agricultural economic outcomes, the FADN data offer an appropriate setting for assessing the performance of a Bayesian spatial small area model.

2 Method and application

To estimate the mean of the local target response parameters based on the sampled area means provided by the direct estimates $y_{i,t}$, $i = 1,...,m$, we adopt an area-level model specified as a time-varying random coefficient model with fixed regressors. We define the multiple-stage model for the random process θ_t at time t:

$$\theta_{i,t} = \mathbf{x}'_{i,t}\beta + u_{i,t}, \quad \theta_{i,t} = \phi\,\theta_{i,t-1} + \alpha_{t-1}, \quad \mathbf{u}_t = \rho_s \mathbf{W}\mathbf{u}_t + \mathbf{v}_t,$$

with $\mathbf{X}_t$ the design matrix of the fixed effects of order $m \times p$, with m as the number of the areas, $\mathbf{W}$ a the spatial weight matrix for the $i = 1,...,m$ subjects, and a matrix $\mathbf{Z}$ as the design matrix of random-area effects for the corresponding m areas, ϕ is a fixed coefficient to be estimated, and α represents the increment in mean of the series. Thus, the simultaneous spatial error process formulation for $\theta_{i,t}$ gives the model:

$$\theta_t = \mathbf{X}_t\beta + \mathbf{Z}\mathbf{u}_t = \mathbf{X}_t\beta + \mathbf{Z}(\mathbf{I} - \rho_s\mathbf{W})^{-1}\mathbf{v}_t,$$

where $\mathbf{Z}(\mathbf{I}-\rho_s\mathbf{W})^{-1}\mathbf{v}_t$ is the random part of $\theta_{i,t}$, $\mathbf{Z}=\mathbf{I}_m$, and ρ_s is the spatial autocorrelation coefficient. In order to obtain more accurate estimates of the means at the province level, outperforming the efficiency direct sampling estimates, the model θ_t is considered as the linking regression model for the local area parameters (the small area means) when integrated with the sampling (observational) model $\mathbf{y}_t=\theta_t+\mathbf{e}_t$, $e_{it}\sim N(0,\sigma^2_{y,i,t})$. Following the Fay-Herriot model and its extensions, the sampling error variances $\sigma^2_{y,i,t}$ are customarily considered to be known in the model introduced. The Hierarchical Bayes (HB) model considered in this study is designed to capture the temporal evolution of the variable of interest as well as its variation across small areas, and is specified as follows:

$$
\begin{aligned}
y_{i,t} &\sim \text{normal}(\theta_{i,t},\sigma^2_{y,i,t}), && \text{Sampling (observational) model}\\
\theta_{i,t} &\sim \text{normal}(\theta_{i,t-1}+\alpha_{t-1},\sigma^2_{\theta}), && \text{Underlying trend}\\
\alpha_{t-1} &\sim \text{normal}(\phi\alpha_{t-2},\sigma^2_{\alpha}), && \text{Increments in mean}\\
\gamma &\sim \text{normal}(x_i'\beta,\sigma^2_{\gamma}), && \text{Area parameters linking model}\\
v_t &\sim \text{normal}(0,\sigma^2_{v}), && \text{Spatial random-area effect}
\end{aligned}
$$

This study focuses on key economic indicators from the FADN dataset that describe farm size and performance and are consistently available across areas and over time. Standard output is used as the main variable of interest, while labour, land, and livestock inputs are included as covariates, allowing for a parsimonious model specification that captures the main drivers of farm economic performance. The analysis considers the period from 2018 to 2022 and focuses on 47 provinces belonging to the North-East and North-West macro-areas of Italy, covering the regions of Alto Adige, Emilia-Romagna, Friuli Venezia Giulia, Lombardia, Piemonte, Trentino, Valle d'Aosta, and Veneto. The random coefficients $\theta_{i,t}$ and α_{t-1} are estimated, giving a representation of the time dependence in the years considered of the evolution of the general average of the standard output indicator in the Northern Italian farms, together with the dynamic small area estimates at the Province level (NUTS3). The Bayesian estimates reflect the spatial and temporal patterns of the sample-based estimates obtained with the direct estimator, while simultaneously providing a more reliable and accurate estimation, as is typical in classical small area estimation models. Therefore, the estimates are not affected by the variability induced by the small sample sizes that may characterize certain areas (see Figures 1 and 2 for a comparison). The proposed model represents a valuable tool for the dynamic assessment of economic policies at the local level and can be readily extended to finer spatial scales than provinces, such as municipalities or other domains not explicitly defined within the sampling design.

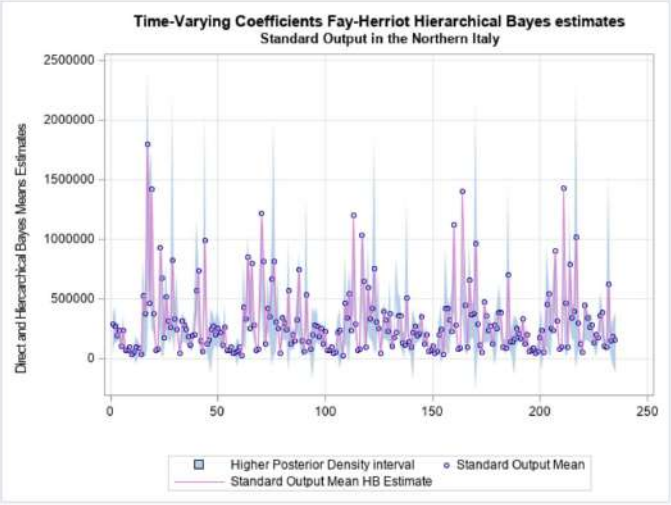

Fig. 1 The comparison between the estimates highlights that the direct estimates fall within the Higher Posterior Density Interval of the Bayesian estimates. On the x-axis, the 47 provinces considered over the five years are represented.

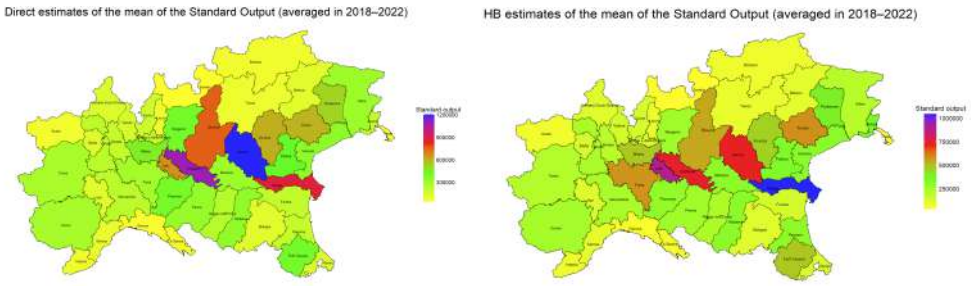

Fig. 2 On the left, the average of the direct estimates for the 47 provinces considered; on the right, the Bayesian estimate obtained with the model proposed in this work. For some provinces, the estimated value differs from the direct estimate, despite the overall trend being nearly identical.

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Machine Learning and the Prediction of Geographically Distributed Data: A Methodological Proposal

Alfredo Cartone, Simone Mazzaferro and Paolo Postiglione

Abstract Although Classification and Regression Trees (CART) are widely used for prediction, they do not exploit spatial information and may therefore underperform in geo-referenced settings characterized by spatial effects. We propose the Spatially Aware Regression Tree (SPART), an extension of CART for continuous responses that incorporates spatial information into the splitting rule through a penalized spatial criterion. The method discourages non-contiguous partitions, thereby accommodating spatial instabilities and improve accuracy. A preliminary application to the Boston housing dataset suggests that SPART outperforms CART in spatial prediction tasks.

Key words: Spatial statistics, Spatial effects, Spatial heterogeneity, CART.

1 Introduction

The Classification and Regression Tree (CART) algorithm is widely used for prediction due to its flexibility and lack of parametric assumptions ([4]). By constructing predictions through binary recursive partitions, CART avoids many challenges typical of linear models ([5]). Its applications span both the natural and social sciences, with extensive use in economics (e.g., [6]).

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Many of these studies involve spatial data, where observations are geographically referenced and spatial effects are non-negligible. Two spatial effects are typically distinguished. Spatial dependence refers to the propensity for observations at one location to be influenced by observations at nearby locations, while spatial heterogeneity captures the instability of statistical relationships across space, often arising from heteroskedasticity or the presence of spatial regimes ([1]). Yet, CART is inherently aspatial and does not incorporate spatial effects.

Existing pioneering approaches focus mainly on spatial dependence ([2], [3]), whereas little attention has been paid to how spatial heterogeneity and local instabilities affect prediction accuracy. In this paper, we propose the Spatially Aware Regression Tree (SPART) method, an extension of CART for continuous outcomes that incorporates spatial information directly into the splitting rule. SPART extends the logic of CART while including a spatial penalty that discourages non-contiguous splits, thereby enabling the analysis of spatial heterogeneity and aiming to improve predictive accuracy.

2 Methods

Let $\mathcal{L}$ denote a set consisting of $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_N, y_N)$, with $\mathbf{X}$ a matrix of $p = 1, \dots, P$ variables and $\mathbf{y}$ a continuous response both measured on $i = 1 \dots N$ units. CART uses the information from $\mathcal{L}$ to predict $\mathbf{y}$ through a binary recursive partitioning algorithm. At each step, the procedure splits a subset of the data set (a node t) into two "child" subsets, the left and right nodes, t_L and t_R. The splitting rule is chosen to maximize within-node homogeneity according to a pre-defined impurity criterion.

Given $f(x)$ as a prediction for y, the value used at a generic terminal node t to minimize $R(t) = \frac{1}{N}\sum_i (y_i - f(x))^2$ is the average of y_i ([4]):

$$\bar{y}(t) = \frac{1}{N(t)} \sum_{x_i \in t} y_i \tag{1}$$

calculated over all the y_i such that $x_i \in t$ and $N(t)$ is the total number of cases into t.

Being Υ the set including any possible split of a terminal node t given the information $\mathcal{L}$, the best split v^* of t is the split in Υ which most decreases dispersion around the mean. For any split v, t is divided into t_L and t_R and we calculate:

$$\Delta R(v, t) = R(t) - R(t_L) - R(t_R) \tag{2}$$

The optimal split $v^* \in \Upsilon$ is selected according to the following rule:

$$\Delta R(v^*, t) = \max_{v^* \in \Upsilon} \Delta R(v, t) \quad . \tag{3}$$

The algorithm then proceeds as follows. The set $\mathcal{L}$ is first assigned to the root node t_0, which contains all observations into a single group. At each subsequent stage $k > 0$,

data are partitioned into increasingly homogeneous subsets by a sequence of binary splits based on any candidate predictor X. Each split is chosen from one of the P predictors from **X**, whereas some predictors may be selected at several steps and others not used at all.

The optimal split is determined as in (4). Each resulting node is then recursively divided into two child nodes, t_L and t_R, and the procedure continues until a stopping condition is met ([6]). Common stopping criteria include a minimum number of observations in a node or a maximum tree depth, where the root node t_0 is defined as level zero.

Standard CART, however, does not use spatial information. To address this limitation, we introduce the SPART method, which incorporates a spatial penalty into the splitting criterion. The new criterion for splitting is:

$$RS(v, t, \beta) = S(t) + \beta\, U(t) \tag{4}$$

where $RS(v, t, \beta)$ combines two components. The first, $S(t)$, is a function based on the sum of squared residuals:

$$S(t) = \frac{\sum_{i \in t_L}(y_i - \bar{y}(t_L))^2 + \sum_{i \in t_R}(y_i - \bar{y}(t_R))^2}{\sum_{i \in t}(y_i - \bar{y}(t))^2} \tag{5}$$

and the second, $U(t)$, is a spatial penalty term computed for each potential split:

$$U(t) = \frac{\sum_{i,j \in t_L} d(i,j) + \sum_{i,j \in t_R} d(i,j)}{\sum_{i,j \in t} d(i,j)} \tag{6}$$

where $d(i,j)$ denotes the generic distance between units i and j, and corresponds to the $(i,j) - th$ element of the matrix **D** of geographical distances. The numerator of (6) measures the total internal distance within the child nodes, while the denominator normalizes this quantity by the total internal distance of the parent node. The hyperparameter $\beta \geq 0$ controls the strength of the spatial constraint and can be selected using k-fold cross-validation ([5]). Both $S(t)$ and $U(t)$ are normalized, unlike in standard CART, which allows their relative contributions to be balanced by β.

Finally, SPART select its optimal split $v^o \in \Upsilon$ as:

$$RS(v^o, t) = arg\ \min_{v^o \in \Upsilon} RS(v, t, \beta) \tag{7}$$

The algorithm then proceeds likewise standard CART, with the key distinction that the spatial penalty favors conterminous child nodes. By incorporating spatial information directly into the objective function, SPART encourages splits v^o that respect underlying spatial structures. This modification allows the algorithm to potentially improve the predictive accuracy of the tree defined by criterion (3).

3 Results

To provide preliminary evidence of SPART in prediction accuracy, we perform an empirical application on the Boston dataset ([4]). The response variable is median housing value for 506 census tracts in Boston, and eight predictors are used: the crime rate, the percent of land zoned for lots, the average number of rooms, the percent of houses build before 1940, the weighted distance from employment centers, the property tax rate, the pupil/teacher ratio, and the percentage of foreign people. To explore performance across different modelling modalities, we compare SPART and standard CART under two maximum tree depth 3 and 8 – representing different level of complexity of the tree, while holding the minimum split size constant at 10. In Table (1) the root of mean squared errors (RMSE) is calculated as $\sqrt{(1/N)\sum_i (y_i - \bar{y}(t))^2}$.

Preliminary results highlight the superiority of SPART over CART for both depth settings, with the relative improvement particularly pronounced for the case of max depth equal to 8 (21% reduction in RMSE). These findings indicate the relevance of considering spatial effects while using machine learning techniques.

Table 1: *RMSE for standard CART and SPART.*

Method	Max depth = 3	Max depth = 8
CART	0.2346	0.1547
SPART	0.2054	0.1220

4 Conclusions

Preliminary evidence indicates that SPART outperforms standard CART for the prediction of economic data that are geographically distributed. Future analyses will explore SPART's properties through simulation studies and assess its robustness under alternative spatial configurations.

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Mapping Skill Requirements in ICT Occupations using an IRT Modelling Approach

Alessandro Gallo, Francesca Adele Giambona, Lucia Buzzigoli and Laura Grassini

Abstract Online Job Advertisements (OJAs) represent a valuable resource for analysing labour market demand in contemporary economies. Using a unique dataset provided by Lightcast for the year 2024, we propose a new approach to classify and map the most relevant skill requirements for ICT occupations focusing on Italian regions. The proposed approach is based on Item Response Theory (IRT) and aims to achieve two main aims. First, it allows to construct an index able to capture, for each job advertisement, the skill requirements. Second, it provides a set of statistical parameters that highlight the most critical skills for specific occupations as well as for the ICT sector as a whole. These results can support the development of targeted economic and social policies, while the skill requirements index can be aggregated and integrated into macroeconomic models to explore its relationship with territorial socio-economic indicators.

Key words: OJAs, Skills, Labour Market, Item Response Theory.

1 Introduction

Online Job Advertisements (OJAs) provide real-time, detailed insights into the skills and requirements demanded by employers, offering a unique lens on Italy's labour market (Giambona et al., 2024). In a country marked by strong regional disparities and evolving economic challenges, analysing OJAs allows us to map skill requirements across sectors and territories, track emerging trends, and assess implications for employment, labour market participation, and economic inequality

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(Deming and Kahn, 2018). The use of Online Job Advertisements (OJAs) is particularly relevant for analysing and tracking the evolution of Information and Communication Technology (ICT) occupations and the associated skills, as they constitute a recruitment channel closely aligned with the preferences of prospective candidates (Kahlawi et al., 2024). ICT occupations are defined using the ESCO[2] 2-digit groups of occupations 25 – *Information and communication technology professionals* and 35 – *Information and communications technicians.* To analyse online job advertisements (OJAs), we use Lightcast data. This dataset provides one of the most comprehensive views of online labour market demand, covering millions of job postings collected daily from a wide range of sources, including specialised job portals and company websites.

This paper contributes to the literature in several ways. First, it introduces a novel approach to measuring and mapping the most important labour market skills across occupations and territorial areas. In addition, the method produces a measure of the average skill requirements demanded within each territory, enabling comparisons across occupations, geographical areas, and over time. Methodologically, the approach builds on the Item Response Theory (IRT) framework, a widely applied probabilistic model for measuring latent traits from categorical or dichotomous data (Kamata & Vaughn, 2011). By adopting a Multilevel Item Response Theory (MLIRT) model (Fox & Glas, 2001), we derive an index of the *skill requirement level demanded in each job advertisement*, supporting the potential longitudinal analyses of the most demanding occupations across the Italian regions. Moreover, this framework allows the estimation of parameters that identify, both analytically and graphically, the skills most critical for each occupation, and territory.

2 Methodology

Following Kamata and Vaugh (2011), the general framework of the MLIRT considers a population of *N* individuals p $(p = 1, \dots N)$, in the group g $(g = 1, \dots G)$, where $N, G \in \mathbb{N}$. The 2PL-MIRT model can be expressed as:

$$P(X_i = 1|\theta_{pg}, a_i, b_i) = \frac{\exp\left[a_i\left(\left(\xi_g + \zeta_{pg}\right) - b_i\right)\right]}{1 + \exp\left[a_i\left(\left(\xi_g + \zeta_{pg}\right) - b_i\right)\right]}. \quad (1)$$

Here, X_i represents the answer for the item i, with $i = 1, \dots K$, and $X_i = 1$ is defined as *correct* and $X_i = 0$ as *not correct*. θ_{pg} denotes the latent trait (ability) of the individual p in the group g, and is expressed as $\theta_{pg} = \xi_g + \zeta_{pg}$, where ξ_g represent the mean ability of group g, and ζ_{pg} is the amount of deviation from the group mean ability for person p in group g. The parameter b reflects the *item's difficulty*, indicating how high θ_{pg} must be for an individual to respond correctly to

[2] ESCO stands for European Skills, Competences, and Occupations, more information are available at https://esco.ec.europa.eu/en

X. The parameter a represents *item's discriminability*, measuring the extent to which X_i differentiates between individuals with varying levels of θ_{pg}. To interpret the estimated parameters, researchers typically use Item Characteristic Curves (ICCs).

In this paper we apply this method by treating each job advertisement as a statistical unit p within its corresponding occupation g (e.g. software developers, system analysts, and so on). This approach is suitable for two main reasons. First, the latent trait can be interpreted as an index of the *level of skills required* in a job advertisement, under the assumption that *a higher number of requested skills reflects a higher level of requirements demanded*[3]. This provides a measure of the requirement level asked in each job ad. These unit level results can be aggregated to produce regional estimates of the average skill requirement demanded across regions, as well as to track trends over time by exploiting the longitudinal nature of the data.

Second, this method allows for the identification of the most relevant skills within each occupation, sector and region using the parameters a_i and b_i. The parameter b_i reflects *skill rarity* (difficulty), indicating the level of the latent trait θ_{pg} required for a job ad to include a specific skill. The parameter a_i captures *skill discrimination*, measuring the extent to which a skill differentiates between job ads with varying levels of θ_{pg}. In other words, a skill with high discriminability is particularly essential for the occupation since it discriminates between a highly demanding position and a less demanding one. Item Characteristic Curves (ICCs) provide a visual representation of these parameters. Each curve corresponds to a skill, where the steepness indicates discriminability and the curve's position along the x-axis reflects the rarity.

3 Data and Descriptive Statistics

This work relies on OJA provided by Lightcast. Lightcast is a private labour market analytics firm specialising in the collection and harmonisation of job vacancy postings, which are used to analyse labour demand patterns, occupational structures, and job requirements. Beyond occupations, the dataset also includes information on skills requested, contract type, education, companies, location, and other information. Most variables refer to official classifications (such as LAU and NUTS for geographical areas), and occupations and skills are traced back to the ESCO taxonomy. We started by considering all the OJAs for the year 2024, leading to a sample composed of 4,439,258 OJAs. We then focused on the ICT occupations, reducing the sample to 148,548 OJAs and 2,476,132 skills. Considering the distribution of OJAs for ICT occupations across Italian regions, the majority of job ads are posted in Lombardia (29.8%), followed by Emilia-Romagna (16.3%) and Lazio (12.7%). Together with Veneto (9.0%) and Piemonte (7.3%), these regions account for approximately 75% of total ICT labour demand. On the other hand, considering the average number of skills requested per OJA, disaggregated by

[3] This may be considered a strong assumption considering a broad ICT sector, however the MLIRT approach mitigates considerably this issue, comparing skills among job ads within the same occupation (within groups g).

occupation (ESCO level 4), provides an indication of which occupations are the most demanding in terms of requirements. Preliminary results from these analysis supports our assumption regarding skill and competencies requirements. Less qualified occupations tend to require fewer skills, such as technician roles with an average of 20 skills requested in each OJA, whereas more highly qualified occupations demand a broader set of skills, such as software, web, and multimedia developers, as well as database and network professionals with an average of 30 requested skills for each OJA.

4 Expected results and Conclusion

This project introduces a novel approach to analysing labour market skills by constructing an index of skill requirements demand. Additionally, the estimation of parameters *a* (*skill discrimination*) and *b* (*skill rarity*) provides new tools to assess skill competitiveness. In line with previous literature (Giambona et al., 2024) and with our preliminary descriptive statistics, results may be expected to reveal the well-documented North–South gradient. Northern regions are expected to exhibit higher levels of skill requirements, whereas southern areas often display the lowest. Nonetheless, we also expect to challenge such "classic" north-to-south divide. It may be anticipated that the main economic hubs will also emerge as the areas demanding the highest levels of skill competencies regardless of the territorial position.
This approach can provide new insights into the analysis of ICT labour market demand. On the one hand, it offers a clearer picture of the most in-demand skills across ICT occupations, from both a regional and an intertemporal perspective. On the other hand, the derived requirements parameter can be incorporated into macro-econometric models to examine its impact on other relevant economic outcomes.

Data Disclaimer: This article reflects solely the results and opinions of the authors and does not necessarily represent the position of Lightcast, which shall not be held liable for its content.

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Mapping the Geography of Innovation and Firm Performance in Italy: A Spatial Approach Beyond Industrial Districts

Alessio Bumbea, Annamaria Giuffrida, Katarzyna Kopczewska and Andrea Mazzitelli

Abstract This study examines the geography of innovation in Italy by comparing traditional industrial districts with clusters obtained through the K-Prototypes algorithm. By integrating geographical, technological, and sectoral proximity, we identify groups of firms that are more internally coherent than standard district classifications. The results show that these data-driven clusters outperform district membership in explaining firm productivity. The study contributes to the debate on the decline of industrial districts by proposing analytical tools better suited to capturing the current structure of innovation in Italy.

Key words: Industrial Districts, K-Prototype, Spatial machine learning, Patents

1 Introduction

Italian industrial districts (IDs) have experienced a process of transformation and fragmentation that has progressively undermined their innovative capacity. Globalization and production delocalization have weakened the territorial proximity related to the Marshallian mode [1], while the integration of leading firms into global value chains has increased asymmetries with local subcontractors, disrupting the

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districts' traditional horizontal structure [2]. International competition and cost-driven strategies have further contributed to productive polarisation and the erosion of local specialisation [3]. As a result, innovation has increasingly shifted toward metropolitan or inter-territorial networks where cognitive and technological proximity prevail over geographical proximity [4]. This study aims to assess whether the traditional district classification remains capable of representing the productive and innovative structure of Italian industry, comparing it with data-driven clusters derived from K-Prototypes algorithms that integrate geographical, technological, and sectoral proximity.

2 Data and Method

We rely on patent data sourced from Orbis Intellectual Property [5], a comprehensive dataset that integrates firm-level business, financial, and legal information with detailed records on intellectual property. We organize patents according to the International Patent Classification (IPC) system developed by WIPO. In this study, we use the 3-digit IPC level to capture firms' technological profiles. We apply the K-Prototypes algorithm to group firms by technological similarity. The k-prototypes algorithm supports both numerical variables (e.g., technological intensities) and categorical attributes (e.g., industry codes). The method minimises dissimilarity within the cluster using a mixed distance measure that combines squared Euclidean distance for numeric features and simple matching for categorical features. This approach is particularly beneficial for our analysis, as it enables clustering firms based on both their technological and structural characteristics, providing more accurate groupings when firms possess mixed attribute types. For our context, as firms are characterised simultaneously by technological features (derived from patent information) and structural attributes (e.g., industry codes). In the next step, we outline the two-step clustering strategy used to map the technological and spatial structure of Italian patenting firms.

3 Results

To capture the broad technological and territorial structure of Italian patenting firms, we first applied K-Prototypes (L1) clustering, assigning a dominant weight to geographical proximity. This reflects the well-established tendency of innovative firms to agglomerate spatially [6], making territorial contiguity a useful indicator of shared capabilities and local knowledge spillovers. The L1 clustering generated broad macro-clusters that combine spatial contiguity with coarse technological similarity. We then focused on one group, labelled Machinery & Industrial Manufacturing, consistent with IPC and ATECO patterns, which shows high technological diversity (Shannon $\geq$ 2.8) and low concentration, calculated using

the Herfindahl-Hirschman index applied to the patents (HHI < 0.14). These features suggest the presence of latent technological subgroups, making it an appropriate candidate for further decomposition. We therefore carried out a second-stage (L2) clustering based on the K-Prototypes algorithm, assigning greater weight to technological and sectoral attributes (IPC 3-digit and ATECO) while reducing the influence of geographical proximity. The objective was to uncover fine-grained patterns of technological specialisation within the broader industrial structure identified at Level-1. Figure 1 shows how the resulting L2 clusters are spatially distributed across the national landscape. The L2 procedure revealed 4 distinct sub-clusters, each characterised by a different technological profile. This result aligns with existing evidence showing that seemingly homogeneous industrial areas often contain multiple, technologically specialised niches [6].

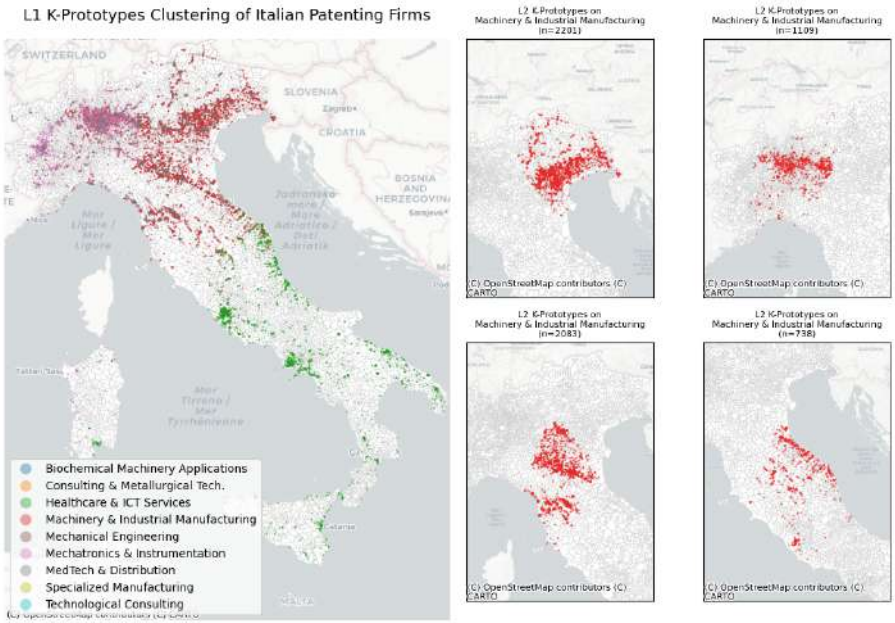

Fig. 1 L1 and L2 K-Prototypes clustering of Italian patenting firms. The left panel shows the L1 clustering, which identifies broad geography-driven macro-clusters. The right panels decompose the Machinery & Industrial Manufacturing group through an L2 analysis, revealing four technologically distinct subclusters concentrated in Northern and Central Italy.

To assess whether firm performance is more closely linked to traditional IDs or to the new clusters identified from the L1 K-Prototypes algorithm, we estimate a fixed-effects regression model separately for firms belonging to the K-Prototypes clusters and for those located within IDs. In both cases, the dependent variable is Labour Productivity, measured as value added per employee, and the specification includes controls for firm size, export status, and group (holding) affiliation, along with two-digit ATECO and NUTS3 fixed effects. When focusing on the fixed-effects specification, patenting is positively and significantly associated with labour productivity among firms in the K-prototypes clusters: the patent coefficient is about

0.047***, s.e. 0.008. By contrast, within IDs the patent coefficient falls to around 0.001 (s.e. 0.005) and becomes statistically insignificant (while it is about 0.076** without fixed effects). Overall, these findings are consistent with the idea that data-driven cluster definitions provide a more economically coherent segmentation than traditional IDs [7].

4 Conclusions

This paper applies a spatial clustering approach to assess whether Italy's innovative capacity remains concentrated within traditional IDs or whether new technological clusters are emerging beyond their historical boundaries. Using K-Prototypes to integrate geographical, technological, and sectoral information, we identify clusters that reveal distinct patterns of specialisation. The findings show that these empirically derived clusters outperform district membership in explaining firm productivity. Future research could further extend this analysis in two directions. First, the regression framework could be enriched by incorporating additional firm-level covariates. Second, the spatial dimension of the relationship between innovation and productivity could be analysed through Geographically Weighted Regression (GWR) [8].

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Nowcasting Public Finance Main Aggregates Using New Data Sources

Fabio Bacchini, Francesca Di Iorio and Roberto Golinelli

Abstract In 2024, the EU Council reformed the framework governing country-specific medium-term fiscal-structural plans, introducing, among other elements, expenditure-based targets for Member States. This reform increases the importance of timely data on key public deficit aggregates, which are currently released quarterly with a delay of approximately 90 days. This paper examines whether established econometric methods, such as MIDAS models or temporal disaggregation, can be used to produce reliable nowcasts of key aggregates of public finance. The analysis relies on available monthly data on government revenues and investment spending.

Key words: Nowcasting, Public Finance, Monthly data source, Temporal disaggregation, MIDAS

1 Motivation

In 2024, the EU Council reformed the European fiscal rules, defining adjustment paths for countries with public debt above 60% of GDP or deficits exceeding 3%. This reform increases the need for timely and accurate monitoring of public finances to detect deviations from sustainable fiscal paths.

Fiscal sustainability analysis is closely tied to GDP and its components, making real-time economic measurement increasingly important. In this context, nowcast-

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ing (Giannone, *et. al* 2008) has gained prominence. European institutions, particularly the European Commission, have shown growing interest in nowcasting for real-time GDP monitoring, inflation forecasting, and regional economic analysis.

Traditional forecasting approaches rely on delayed official data and are often not timely enough for real-time policymaking. Nowcasting overcomes these limitations by combining high-frequency information with econometric techniques to deliver timely insights on the state of public finances. Despite extensive research on macroeconomic nowcasting (see, among others, Baffigi *et al.* 2004, Banbura *et al*. 2013, Kuzin *et al.* 2011, Dauphin *et al.* 2022, Barbaglia *et al.* 2025), its application to public finance remains limited. Monthly fiscal data are scarce, and monitoring typically focuses on the deficit rather than on its underlying components, such as revenues and public investment.

With reference to Italy, one of the largest European countries for which expenditure targets have been elaborated, this paper addresses the informational gap by applying nowcasting methods directly to key public finance variables, such as direct and indirect tax revenues and public investment expenditure, assessing whether well established techniques, e.g., MIxed-DAta Sampling (MIDAS) models, can produce reliable nowcasts of these components. The paper also explores whether these nowcasts can be used for fiscal scenario analysis within a framework inspired by the MeMo-It model developed by Istat (Bacchini *et al.*, 2013).

2 Data source

The Italian aggregates on public finance are disseminated quarterly from Istat inside the Sector accounts, according to the scheme provided by Sec 2010 (paragraphs 20.68-20.72). These indicators are usually available at + 90 days from the reference period, while the full disaggregation with more delay.

Quarterly institutional sector accounts are based on the same definitions as annual accounts but are compiled with much less detail. To address this limitation, statistical offices rely on econometric methods, especially temporal disaggregation, which assumes that the relationships observed at the annual frequency between variables and suitable indicators also apply at the quarterly level. This approach allows annual data to be distributed across quarters and extended beyond the most recent complete year.

In the context of new European fiscal regulations, there is a growing need to monitor expenditures and revenues more frequently with their pivotal aggregates.

To this end, the Information System on Public Entities' Operations (SIOPE), developed by the State General Accounting Department, represents a key data source. Established under Law No. 289/2002, SIOPE electronically records public administrations' revenues and expenditures with the aim of improving the quality and transparency of public accounts. SIOPE includes payment data processed by the Bank of Italy on behalf of the State, as well as daily reports from the banking treasurers of other public administrations.

Among the many items recorded in SIOPE, particular attention is given to monthly municipal investment payments. The information set is extremely large, containing about 8 billion records per year, of which roughly 7 billion relate to municipalities and provinces. In 2023 alone, around 56,000 records specifically referred to municipal and provincial investment expenditures.

On the revenue side, the Ministry of Economy and Finance publishes monthly detailed data on tax revenues by major categories. These data allow for the analysis of monthly flows of direct and indirect taxes, including taxes on income and wealth, as well as taxes on production and imports. Key components such as personal income tax (IRPEF) and value added tax (VAT) are also available, along with other taxes such as excise duties, stamp duties, and fuel taxes. On average, personal income tax accounts for about 80% of taxes on income and wealth, while VAT represents roughly 50% of taxes on production and imports.

3 Nowcasting strategies

The monthly sources on revenues and investment allow for a nowcasting strategy to be followed to estimate the amount for the current year of the main variables of interest, such as taxes on production and imports, current taxes on income and wealth, and public investments. The monthly sources are characterized by notable seasonality due to the payment schedule. The paper considers two possible nowcasting alternatives: a Chow-Lin Temporal Disaggregation (TD)-based strategy and a MIDAS-based strategy.

A TD-based strategy can be summarized as follows:

1) For each quarterly target variable y, select the monthly indicator X that mostly affects target's dynamics
2) Seasonally adjust X and forecast it until the end of the current year
3) Chow-Lin (CL) temporal disaggregation of y at monthly frequency y_m using the seasonally adjusted X to obtain a forecast of y_m until the end of the year. To account for y seasonality, seasonal dummies in CL.
4) The sum of y_m monthly estimates for the current year provides the annual nowcast (the sum of the monthly estimates for the available quarter satisfies the constraint by construction)

In the MIDAS approach, the Low frequency dependent variable y_t^L is regressed on a distributed lag of the High frequency x_t^H. Our analysis considers the unrestricted MIDAS (U-MIDAS) as proposed by Foroni et al. (2015) which does not resort to functional distributed lag polynomials. The U-MIDAS model from quarterly to annual data (4 parameters) can be defined as:

$$y_{t+1}^L = a_1 + h_1 y_t^L + c_1^0 x_t^H + c_1^1 x_{t-1/3}^H + c_1^2 x_{t-2/3}^H + \varepsilon_{t+1}^L$$

A possible MIDAS-based strategy can be summarized as follows:

- Once the monthly indicator is available (say in January) use it in the U-MIDAS to obtain the quarterly estimate (say of the first quarter).
- Compute three different nowcasts for the first quarter related to the availability of January, February and March.
- The process is repeated for each quarter (the previous quarter is now entering the U-MIDAS estimation).
- The three different nowcasts for the first quarter in a U-MIDAS that links quarterly to annual data, and provides three different annual estimates.
- The process is repeated for each quarter (the previous quarter now enters in the U-MIDAS estimation). Overall, in one year we have a total of 12 nowcasts.

The performance of the proposed procedure for Taxes on income and wealth, for taxes on production and for Government investments for 2024, and a forecast exercise for 2025 gives encouraging results. However, they are still not satisfactory for an effective monitoring procedure, as both approaches need to be extended to additional quarterly/annual targets beyond those presented in this analysis, and we also need further robustness checks of alternative MIDAS specifications.

For this, we plan to run a predicting-ability horse-race of alternative MIDAS settings against the CL benchmark approach on the basis of both RMSE and MAE.

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Open Manager: a study to confirm managerial implications

Tullio Menini

Abstract The job market and today's society are undergoing deep changes, driven by globalization and digitalization, which are happening at an increasing pace, making necessary to rethink leadership models and managerial competences of those involved in such jobs. In this context, the figure of the Open Manager has emerged, a leader capable of interpreting and promoting the values of collaboration, openness, network building and enhancement of their own team. Our work fits into this transformation, proposing an evaluation model aimed at identifying and developing the typical skills of the Open Manager, using a specific questionnaire built on solid theoretical foundations and tested across various business sectors, as a practical tool to profile managers and foster the spread of a new managerial culture.

Key words: Differential Item Functioning, Open Manager

1 Introduction

Specifically, the research began in 2020 and aims primarily to profile a new managerial figure, the Open Manager, by developing both an evaluation tool and a specific training model to support managers. The studies conducted (Bruttini et al. 2024; Bruttini et al. 2025) have confirmed on the one hand the actual emergence of a managerial profile closer to the culture of the Open Manager, and on the other hand the need to continue creating a new managerial culture, one that aligns with the ongoing cultural and technological transformations. The work evaluates different classification models applied to the results of the questionnaires, which reinforce certain "personas", meaning research-based profiles representing key figures,

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emerged from the methodological analysis. We recommend using these personas and their assignment as a classification tool for future submission of the questionnaire, in order to associate each new manager under investigation with the most relevant managerial profile.

In this contribution, new managers are interviewed using the questionnaire, with the double aim of verifying the generalization of the work through some methodological tools, such as the analysis for Differential Item Functioning (DIF), and of measuring the level of Openness in a new group of managers, comparable to the original reference group. The goal is to assign each individual a level of Openness based on the same metric previously built and validated, and to confirm the managerial implications arising from the classification. This work is the result of a joint research effort by a group including P. Bruttini, P. Mariani, T. Menini, C. Sartirana.

2 Delphi Study in Collectible Design

The aim of this work is the validation of a questionnaire for business managers regarding managerial styles, developed and tested within the Open MOOd research project funded by Fondimpresa since 2020, and its use to identify the level of Openness in newly interviewed managers, to identify the key differential characteristics of Open Managers. The motivation for this work is to offer a reliable and replicable model for evaluating managerial styles, useful both for research and for companies wishing to invest in the development of a new managerial culture oriented towards Open Leadership. The validated questionnaire serves as a starting point for future investigations, training interventions, and growth pathways, in line with the evolving needs of the labour market.

The rapid transformation process due to globalization and digitalization makes it essential to adjust the managerial approach to the evolving society and job market, responding to new needs and new modalities. Some modern developments, such as the use of massive online platforms, the widespread and transversal presence of data, or open-source movements, have increasingly contributed to transforming the dynamics of innovation and the concept of open innovation. Open innovation is becoming increasingly present in literature, as well as in the business and industrial world. It is moving beyond its traditional placement in the R&D departments of large companies and spreading across various sectors and companies of different sizes and histories. In this context, the new managerial figure of the Open Manager is increasingly emerging. This leader operates according to the principles of collaboration, openness, networking, and the empowerment of their own team, promoting trust and autonomy, and using digital technologies as enabling tools for collaboration and innovation.

The result of the analysis is used to evaluate hypotheses regarding the characteristics of managers, as previously identified in Bruttini et al. (2024), in relation to the response model related to the item “Regarding the characteristics of the Open Manager, within your company, how close do you feel to this value?”.

This element is evaluated on a scale from 1 to 10, and the results suggest that self-assessments are closely aligned with the measures estimated using the Partial Credit Model (PCM).

A comparison is made with the results of the first analysis conducted by Bruttini et al. (2024) using the new dataset, which outlines six distinct groups of managers showing behaviours similar to those emerged in the first submission, based on their responses to the questionnaire. By juxtaposing the distribution of responses to the questions within each group with the aggregated dataset, the study shows the different levels of openness that characterize each managerial group.

3 Conclusions

This research has validated the OPEN MOOd Questionnaire through a psychometric analysis process based on the Rasch model with item anchoring procedure and systematic DIF verification. The results converge toward conclusions of significant scientific and practical importance.

The total absence of bias (DIF = .00) and the homogeneity of distributions between the two groups demonstrate first and foremost that the instrument measures the "Openness" construct in an equitable and invariant manner across different cohorts, representing a solid methodological foundation for comparative and longitudinal investigations. Intergroup comparability is guaranteed on a solid psychometric basis, which allows attributing to each manager, regardless of cohort membership, an Openness profile on the same reference metric. Managerial profiles are furthermore interpretable and robust for future administrations, as the psychometric stability of the instrument has been empirically confirmed.

This robustness opens the possibility of conducting longitudinal monitoring on a shared and stable metric, allowing to track the evolution of Openness levels over time and evaluate the impact of training programs. Overall, these results support the validity of the Open Manager figure as a psychological construct and provide a solid empirical foundation for the development of the training model and for the implementation of managerial development programs consistent with current cultural and technological transformations.

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Predicting Firms Market Value in Italy: The Role of Environmental Scores

Luca Patelli, Daniele Tintore, Peter Cincinelli, Daniele Toninelli and Giovanna Zanotti

Abstract This study investigates the ability of two tree-based Machine Learning models (Random Forest and XGBoost) to predict the market value of Italian listed firms. The study employs a dataset comprising 71 non-financial companies observed between 2019 and 2023. The adopted models are benchmarked against linear regression in terms of predictive performance; they are interpreted using SHAP values and Rank Graduation Explainability. The results show that the predictions are primarily driven by financial metrics, with environmental scores playing a marginal role.

Key words: Corporate market value, ESG, prediction, explainability

1 Introduction

The relationship between ESG performance and corporate metrics, such as Corporate Financial Performance (CFP) or Market Value (MV), has attracted growing managerial and academic interest. However, empirical evidence remains mixed due to differences in adopted methodologies, variables, and analyzed contexts [6]. Recent research increasingly relies on Machine Learning (ML) methods to improve

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prediction accuracy [5, 7]. However, increased accuracy often comes at the expense of interpretability, as complex and nonlinear structures may obscure the contribution of individual predictors.

This study addresses the following research questions: Do ML models predict the market value of Italian listed firms better than a linear regression approach? What role does environmental performance play in these predictions? In order to answer these questions, we compare a linear regression benchmark with Random Forest (RF) and XGBoost. Moreover, with the purpose of combining predictive performance with transparent valuation insights, we evaluate results using Shapley Additive exPlanations (SHAP) and Rank Graduation Explainability (RGE).

2 Data and methods

Our analysis considers Italian listed companies observed annually over the period from 2019 to 2023. Data were extracted from AIDA, ORBIS, Refinitiv (LSEG), and Factset. Starting from 144 listed Italian companies, we excluded financial institutions, and firms with missing Environmental Pillar scores, obtaining a final sample of 71 firms (355 firm-year observations). We focus on a single-country setting to increase homogeneity and reduce possible confounding effects.

The dependent variable is a proxy for market valuation: Tobin's Q. This indicator measures the ratio of market capitalization on total assets. The list of predictors includes a mix of traditional financial ratios and an environmental indicator: Leverage (`LEV`): Total debt divided by total assets; Return on Assets (`ROA_pc`): the percentage of net income on total assets; Asset Efficiency (`Rev_TASS_pc`): the percentage of total revenue on total assets; Current Ratio (`Current_Ratio`): Current assets divided by current liabilities; Interest Coverage (`OF_EBITDA_pc`): Interest expenses as a percentage of EBITDA; Environmental Pillar Score (`ENV_S`): ESG-based score of environmental performance from Refinitiv.

To capture potential nonlinearities and interactions among studied variables, we adopted RF [3] and XGBoost [4]. These models' predictive performances are compared with OLS results. Specifically, by means of a Hausman test we assessed the necessity of fixed effects. As the test indicated no significant bias from unobserved heterogeneity, we applied the ML models to the full panel without imposing a fixed-effects structure.

Model interpretation relies on native Variable Importance (VI) measures. For RF, the percentage increase in Mean Squared Error (%IncMSE) was selected. This metric quantifies the importance of a predictor as the increase in out-of-bag MSE when the predictor's values are randomly permuted. Conversely, for XGBoost, VI was evaluated using Gain, which reflects the marginal contribution of each predictor in reducing the loss function across all splits. To enhance the interpretability of the ML methods used, the analysis also included SHAP values [8] and the RGE [2]. SHAP values, grounded in cooperative game theory, provide a measure that quantifies the marginal contribution of each predictor across multiple possible coalitions

(i.e., combinations of predictors). Complementary, the RGE framework employs rank-based metrics derived from the Lorenz curve to evaluate the concordance between predicted and observed rankings. Specifically, RGE takes into account the differences in ranks obtained from the full model and from the model without the j-th predictor. This offers a robust assessment of model explainability and fairness.

3 Preliminary Results

The results are obtained using a leave-one-year-out cross-validation (5 folds, one year held out per fold). The predictive performance of RF and XGBoost, when compared to OLS, is encouraging. Specifically, the Root Mean Square Error (RMSE) of RF is 0.46, the Mean Absolute Error (MAE) is 0.32, and the R-Squared (R^2) is 0.51. XGBoost's performance is marginally lower (RMSE=0.48, MAE=0.33, R^2=0.46). In both cases, the metrics are better than those obtained using the OLS estimation: RMSE=0.57, MAE=0.42 and R^2=0.26.

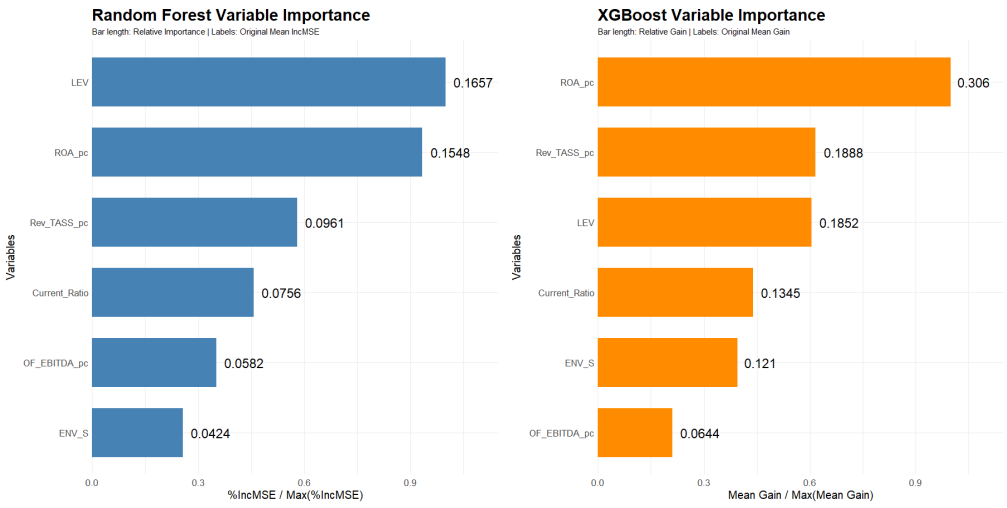

Fig. 1: Variable importance (5-fold CV).

About the VI, Fig. 1 shows that `ROA_pc`, `LEV` and `Rev_TASS_pc` are the most relevant predictors for both models, whereas `ENV_S` is the least influential in the RF model and it retains a low-to-moderate relevance in XGBoost. Table 1 confirms this: `ROA_pc` attains the largest average absolute SHAP (RF 0.147; XGBoost 0.168) and RGE (RF 0.028; XGBoost 0.041) values, while `ENV_S` shows smaller contributions (SHAP: RF 0.055, XGBoost 0.076; RGE: RF 0.012, XGBoost 0.023). For OLS, `ROA_pc` and `LEV` have also been identified as the primary predictors. However, the ranges of both SHAP values and RGE are larger in OLS than in RF and XGBoost. In particular, RGE values span 0.001–0.106 in OLS, 0.010–0.029 in RF

and 0.008–0.041 in XGBoost, meaning that no single predictor dominates and predictors typically shift predicted ranks only modestly.

Overall, model explanation is largely driven by profitability and leverage, while environmental sustainability score contributes consistently, but does not act as a primary driver. Notably, OLS's SHAP and RGE for `ENV_S` are numerically closer to RF than to XGBoost, indicating that the linear and RF approaches attribute similar importance to the environmental dimension. This encourages the use of ML for informed predictive purposes, as these methods return a better predictive performance.

Future research is needed, for example focusing on the disaggregation of `ENV_S` into specific environmental dimensions (i.e., environmental investments, emissions and resource use), examining cross-sector heterogeneity, and extending the analysis to a broader international context (e.g., focusing on European companies).

Table 1: 5-Fold CV Averaged Absolute SHAP values and RGE

Variable	OLS		Random Forest		XGBoost	
	SHAP	RGE	SHAP	RGE	SHAP	RGE
ROA_pc	**0.181**	**0.106**	0.147	0.029	0.168	0.041
LEV	**0.120**	**0.049**	0.114	0.025	0.115	0.036
Current_Ratio	0.023	0.002	0.070	0.014	**0.083**	**0.027**
OF_EBITDA_pc	0.004	0.001	**0.064**	**0.010**	0.041	0.008
Rev_TASS_pc	0.038	0.005	0.064	0.016	**0.085**	**0.029**
ENV_S	0.050	0.010	0.055	0.012	**0.076**	**0.024**

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Public cultural spending and the quality and diversity of leisure consumption

Cristina Bernini and Federica Galli

Abstract This paper examines the impact of public cultural expenditure on the diversity and quality of leisure spending in Italy. Using microdata from the ISTAT Household Budget Survey (2014–2020), we construct indices of spending diversity and quality as proxies for cultural participation. Our results show that higher public cultural spending is positively associated with both broader and higher-quality engagement in cultural and recreational activities. These findings highlight the role of cultural policy in promoting inclusive access to culture.

Key words: Cultural consumptions, Spending quality and diversity, Public cultural spending.

Funding: This study was funded by the European Union -NextGenerationEU, Mission 4, Component 2, in the framework of the GRINS -Growing Resilient, INclusive and Sustainable project (GRINS PE00000018 – CUP E63C22002120006). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

1 Introduction

Enhancing access to and participation in cultural activities has long represented a core policy objective across both Europe and North America, reflecting the widely recognized benefits of cultural engagement for health and well-being (Baldin and Bille, 2023) as well as for education and individual empowerment (Skot-Hansen, 2005). Furthermore, individuals tend to derive greater satisfaction from spending on

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life experiences, such as travel, dining, and cultural activities, than from purchasing material goods like clothing or jewelry (Yang and Mattila, 2017).
Extensive research has concentrated on the factors that shape cultural spending, finding that preferences for specific cultural goods are strongly associated with social group affiliation (Notten et al., 2015) and with human capital, including both education and arts-related training (Ateca-Amestoy, 2009). Moreover, also the spatial context also plays an important role. Pawlowski and Breuer (2012), for example, found that in Germany, city size, urban–rural differences, and transportation costs significantly influence the frequency of attendance at cultural events. Similarly, Rössel and Weingartner (2016) showed that the availability and quality of cultural infrastructure affect cultural consumption patterns in Switzerland.
Despite extensive research explores the determinants of cultural participation, the impact of public cultural spending remains underexplored, with just some evidence from Italy suggesting that investments in leisure and welfare services enhance citizens' well-being and quality of life (Mafrolla and D'Amico, 2016; Meliciani and Terzo, 2024). In this paper, we investigate the link between public cultural expenditure and cultural participation, employing Italian expenditure data to construct measures of spending quality and diversity, used as proxies for cultural participation. In particular, spending diversity and quality provide complementary measures of cultural participation, capturing both its extensive dimension (breadth of engagement) and its intensive dimension (quality and depth of cultural involvement). The results are expected to offer valuable insights for policymakers in designing evidence-based cultural and social policies, promoting inclusive access to cultural opportunities.

2 Data

We use data from the ISTAT "Household Budget Survey" (HBS) from 2014 to 2020. According to the COICOP (2018) classification, leisure spending is disaggregated into the Recreation (*Recr*) and Culture (*Cult*) subcategories. *Recr* includes four groups of expenditures: recreational goods, such as board and video games, toys, and sports equipment; recreational services, including participation in sports events, and use of recreational facilities; recreational durables, covering durable goods like televisions, cameras, and personal computers; and finally, gardening and pets. The Culture category comprises: books, which include expenditures on books, newspapers, magazines, and stationery; cultural goods, such as musical instruments, CDs, and DVDs; and cultural services, which refer to spending on live performances, theatre subscriptions, and visits to cultural or natural heritage sites. The remaining items mainly relate to tourism, encompassing school trips, and domestic and international travels, which is out the scope of this paper.

3 Method

To capture broader access to cultural opportunities, and a more engaged and participatory cultural lifestyle, we consider the Spending Diversity Index (DI). For each unit i and leisure subcategory c, where c ∈ {Recr, Cult}, the DI index, computed using the Gini–Simpson approach, is defined as

$$DI_{i,c} = \sum_{j^c} w_{ij}\left(1 - w_{ij}\right) \tag{1}$$

where w_{ij} represents the share of spending allocated to the j-th sub-subcategory within subcategory c. A higher value of $DI_{i,c}$ indicates a more diversified spending pattern, suggesting a broader engagement with different types of leisure activities.
Moreover, to capture preferences for more exclusive or enriching experiences which are often linked to socioeconomic status, education, and access to infrastructure, we consider the Spending Quality Index (QI), following the approach proposed by Clements and Gao (2012). QI equals

$$QI_{i,c} = \sum_{j^c} w_{ij}\left(\eta_{ij} - 1\right)\left(\hat{q}_{ij} - \hat{Q}_i\right) \tag{2}$$

where η_{ij} denotes the expenditure elasticity obtained from Engel curve estimations, $\hat{q}_{ij}$ represents the deviation of individual expenditure on the j-th sub-subcategory from the sample mean, and $\hat{Q}_i$ is the deviation of total leisure spending from its average. Positive values of $QI_{i,c}$ indicate that individuals allocate relatively more resources to goods or services with higher income elasticity, thus signaling higher-quality or more aspirational consumption patterns.
To assess the impact of municipal cultural investment on the diversity and quality of leisure spending, we estimate random-effects models where the dependent variables are alternatively DI and QI. The key explanatory variables are per capita public expenditures on cultural and social services, drawn from ISTAT municipal statistics. Control variables include average household income and measures of cultural infrastructure, such as the number of museums and public archives, capturing local opportunities for cultural participation. The analysis is performed at the urbanization-by-region level, the highest geographical granularity available in the HBS data.

4 Results

The estimation results, reported in Table 1, indicate that cultural expenditure is positively associated with both the quality and diversity of spending in cultural and recreational goods. Regarding social public spending, we observe positive coefficients for multipurpose social expenditure linked to recreational activities, while spending targeted at poverty reduction shows a negative association with both cultural

and recreational indices. This pattern likely reflects the fact that poverty-related social expenditure is concentrated in disadvantaged areas, where households tend to allocate fewer resources to cultural and recreational activities to prioritize basic needs.

Table 1: Estimation results

	Cult				***Recr***			
	DI		***QI***		***DI***		***QI***	
CultExp	0.91	***	0.59	***	0.90	***	0.62	***
SocialExp_Family	-0.62	**	0.26		-0.34		-0.23	
SocialExp_Elderly	0.26		-0.08		0.23		0.07	
SocialExp_Poverty	-0.26	**	-0.50	***	-0.33	***	-0.39	***
SocialExp_Multipurpose	0.10		-0.02		0.18	*	0.20	**
Controls	yes		yes		yes		yes	

5 Conclusions

In this paper, we analyzed the role of public cultural expenditure in shaping the diversity and quality of leisure spending. Our results indicate that higher public investments in culture are positively associated with both broader access to cultural opportunities and stronger preferences for more exclusive or enriching experiences. Future extensions of this work will address potential endogeneity between individual and municipal cultural spending and explore additional outcome variables related to subjective well-being and quality of life.

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Quantifying Uncertainty in Cultural Markets: Delphi Approaches for Forecasting and Decision Support

Laura Benedan, Federica Codignola and Paolo Mariani

Abstract This study proposes a methodology for designing a Delphi study in the field of collectible design. A review of the literature on studies that have applied the Delphi method in the arts and cultural heritage sectors was conducted, analysing methodological strategies, panel composition, expert selection criteria, iterative cycles and consensus-building mechanisms. To complement the review, three in-depth interviews were conducted with experts in the field, which were useful for contextualising and refining the key issues related to collectible design. Based on this input, a questionnaire was developed and administered for an original Delphi study. The approach adopted highlights the effectiveness of the Delphi method in supporting strategic forecasting, decision-making and scenario planning in the contexts of creative design and emerging sectors.

Key words: Delphi method, Cultural Heritage, Collectible Design, Expert Consensus

1 Introduction

Traditional economic analysis often struggles to model cultural markets, where symbolic value, qualitative judgment, and limited historical data dominate price

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formation. In such contexts, structured expert elicitation represents a viable alternative for reducing uncertainty and supporting evidence-informed decision-making. The Delphi method, based on anonymous and iterative aggregation of expert judgments, provides a framework for measuring convergence in domains characterized by interpretive authority and data scarcity. Its application is particularly relevant to the collectible design sector, where rapidly evolving aesthetic paradigms, reputational hierarchies, and limited transparency in valuation complicate conventional economic analysis. By enabling structured foresight while limiting institutional bias, Delphi offers a methodological tool for transforming dispersed expertise into measurable indicators. This makes it suitable for investigating emerging dynamics in creative markets, including sustainability concerns, digital-physical hybridity, and evolving collector behaviors.

2 A Narrative Review of Delphi Studies

A narrative review of 11 Delphi-based studies in cultural heritage and related creative sectors was conducted to identify recurrent methodological patterns and statistical practices. The review focused primarily on panel composition, expert selection criteria, consensus thresholds, and the quantitative instruments used to structure expert judgment. Across the examined studies, the Delphi method was consistently implemented through iterative rounds supported by structured measurement tools such as Likert scales, interquartile ranges (IQR), median-based rankings, and, in some cases, fuzzy scoring techniques. In several applications, Delphi outputs were integrated into hybrid decision-support frameworks (e.g., Delphi combined with Analytic Hierarchy Process), highlighting its flexibility in transforming qualitative expertise into structured and decision-relevant indicators.

The literature also confirms the method's relevance for strategic foresight and scenario planning in cultural institutions and art markets. Empirical applications demonstrate the use of convergence measures and probability-weighted evaluations to support institutional strategy and policy decisions. (e.g., Hanson, 2020; Howard et al., 2016; Skender & Dubovicki, 2025; Pan et al., 2025; Pauget et al., 2019; Upadhyaya, 2023).

Regarding panel composition, consistent patterns emerge: expert reputation and professional experience represent the primary selection criteria, while panel structures are typically interdisciplinary, combining academics, practitioners, and institutional actors. Direct identification of experts is generally preferred over snowball techniques, ensuring greater methodological control. The increasing inclusion of heterogeneous competencies reflects a broader shift toward socio-technical conceptions of cultural value.

Overall, the review provides a methodological benchmark for designing a Delphi study in collectible design, ensuring alignment with established statistical practices, while adapting them to the specific characteristics of emerging cultural markets.

3 The Application of the Delphi Study in Collectible Design

The review of prior Delphi applications in cultural heritage and related domains allowed to delineate a research process to develop a Delphi study for the collectible design field, particularly regarding panel size, expert selection, role diversity, and consensus-building practices.

Building on the literature, three in-depth interviews were conducted with experts in collectible design, curatorship, and market analysis. These helped refine the research focus and informed the questionnaire. The interviews emphasized the need to address cross-disciplinary value formation, criteria for collectible significance, and emerging challenges such as sustainability and digital integration.

The Delphi panel composition demonstrated a congruence with the findings of previously reviewed studies. The selection of experts was based on their professional reputation, experience, and institutional credibility, reflecting an increasing inclusion of heterogeneous roles and competencies. This incorporation mirrors the increasing interdisciplinary orientation in contemporary Delphi research. The integration of a narrative review and expert interviews established a substantial foundation for the development of a new Delphi questionnaire in the collectible design field.

This methodological approach ensures consistency with established practices while remaining responsive to the specific characteristics and evolving challenges of the domain.

4 Results of the Delphi Application

The Delphi study involved a panel of approximately 20 experts, selected according to reputation, institutional affiliation, and years of professional experience. The process consisted of two iterative rounds, allowing the measurement of opinion dispersion and convergence.

In the first round, experts evaluated key dimensions of collectible design (e.g., valuation criteria, sustainability relevance, future market drivers) using a 5-point Likert scale. Measures of central tendency and dispersion were calculated, including median and interquartile range (IQR). Results indicate that: (i) consensus was reached on the importance of cross-disciplinary valuation criteria (median ≥ 4; IQR ≤ 1), (ii) sustainability emerged as a moderately convergent dimension (median = 4; IQR = 1.5), and (iii) greater dispersion was observed in forecasts related to AI integration and digital-physical hybridity (IQR ≥ 2). In the second round, feedback was provided to participants, allowing reassessment. A reduction in dispersion was observed across most items, with average IQR decreasing by approximately 35-40%, indicating progressive convergence of expert judgments. These findings demonstrate the capacity of the Delphi method to transform qualitative expertise into structured and progressively convergent judgments, supporting strategic foresight in uncertain cultural markets.

Table 1: Summary of Delphi convergence

Dimension	Round 1 Median	Round 1 IQR	Round 2 IQR	Convergence
Valuation criteria	4	1.0	0.5	High
Sustainability	4	1.5	1.0	Moderate
AI & Digital	3	2.0	1.5	Low-Moderate

Source: author's elaboration

5 Conclusion

The empirical results confirm that the Delphi method provides measurable convergence in expert evaluations within the collectible design sector. Beyond its theoretical suitability, the application demonstrates its operational capacity to structure uncertainty through statistical indicators such as median and interquartile range. The study therefore contributes not only a methodological framework, but also empirical evidence supporting Delphi as a quantification tool for cultural markets characterized by symbolic value and data scarcity. Future developments include additional rounds and the integration of complementary decision-support models.

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Short-time predictions of the Industrial Production Index using subjective expectations of the manufacturing companies

Andrea Marletta, Daniele Pirotta and Biancamaria Zavanella

Abstract Dealing with official data, the problem of delays in the publication of provisional estimates is a very actual topic. This paper studies the time series of the Industrial Production Index in Italy proposing a short-term prediction method achieved using the subjective judgments on the future of the stakeholders of the manufacturing companies. Many studies have attempted to provide forecasts of the future trend of this indicator using different statistical models based on possible relationships with other micro- or macroeconomic variables. From a methodological point of view, an approach for multivariate time-series is proposed, searching for a co-integration link between the analysed time series.

Key words: Cointegration tie, confidence indicators, Industrial Production Index, subjective forecasts

1 Introduction

The main goal of this paper is to use data from the business confidence survey, which are published very promptly (monthly at time t, data for t-1 are available), to

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try to partially overcome the time lag in the data published for the industrial production index (generally, at time t, only data up to t-3 are available).

The general Industrial Production Index (IPI) measures the change over time in the physical volume of production in the industrial sector, defined in the strict sense (i.e., excluding the construction sector). It is based on a monthly statistical survey conducted among businesses, which provide detailed information on the production of specific goods. The index is well known and its data are continuously disseminated by newspapers and radio and television news programs, as well as being used in hundreds of scientific studies. On the other hand, data on business confidence are less well known and less widely disseminated, but they are very important because entrepreneurs are often able to pick up on certain signals from the economic system, unlike statistical models, which are unable to anticipate unexpected events.

In particular, among the qualitative surveys, the focus is on Istat Economic Sentiment Indicator (IESI). Since June 2012, Istat has been publishing a composite indicator of confidence in the entire Italian manufacturing sector [2].

The main idea behind this innovation is to use production expectations for the next three months as a possible leading indicator directly linked to the IPI. By making this link explicit, it is possible to use it to make short-term forecasts of the IPI. Before researching the link between production expectations and the IPI, it is necessary to ensure that these expectations are consistent with the assessments in the same survey. This consistency could be verified using an approach based on the classification of turning points in a time series. If this consistency between assessments and expectations is verified, it is possible to research a long-term relationship between expectations and the IPI.

The paper is organized as follows. Section 2 introduces the steps of the proposed approach presenting the turning point theory, the multivariate time series techniques and forecast methods. Section 3 presents the application of the approach to the Industrial Production Index. Finally, Section 4 is reserved to discussion and final remarks.

2 The proposed approach

In this contribution, to define a turning point, the approach proposed by Naik and Leuthold [5] will be followed, not only for the classification of the time series points but above all for the computation of the indexes measuring the coherence in movements of two or more series. This choice is motivated by the fact that the authors are primarily interested in investigating the presence of co-movements between the IPI and the expectations on the confidence climate indicator. According this approach, each time-series point can be classified as a turning point in 4 categories: a peak when it is preceded and followed in its immediately before and after moments by lower values; a trough is defined when it is preceded and followed in its immediately before and after moments by higher values; an upward is obtained when the value of the series in the previous point is lower and in the next point is

higher; finally a downward is present when the value of the series in the previous point is higher and in the next point is lower.

The theory of turning points is useful to measure the coherence between assessments and expectations. If this coherence is verified, then it is possible to search for a long-term relationship between the expectations and the IPI.

To follow this purpose, a well-known approach of multivariate time-series is proposed, searching for a co-integration link between the two considered time-series. Once obtained this long-term relationship, the latter is used in combination with the expectations of the entrepreneurs to obtain the short-term forecasts. The cointegration vector is obtained through the estimation of a Vector Error Correction Model and the application of the Johansen test [3,4]. Once estimated the cointegration vector measuring the long-term relationship between the expectations and the IPI, the Box-Jenkins procedure has been used to obtain forecasts [1]. This approach provides forecasts through an ARIMA (Auto-Regressive Integrated Moving Average) model. Finally, substituting these forecasts and the data about the expectations for the next three months in the equation representing the cointegration vector, it is possible to obtain prediction of the IPI for the next three months. Let y the cointegration vector, then:

$$y = IPI + \beta * expectations$$

forecasts for IPI are obtained as:

$$IPI_{t+1,\ t+2,\ t+3} = y_{t+1,\ t+2,\ t+3} - \beta * expectations_{t+1,\ t+2,\ t+3}$$

where β is the cointegration coefficient and $expectations_{t+1,\ t+2,\ t+3}$ are the values declared by entrepreneurs in the last 3 months for the future.

3 Results and Conclusions

The proposed approach has been applied on the two time-series from 2010 to 2024. The preliminary results show a similarity between judgments and expectations of the manufacturing companies about the production. This is a mandatory condition to use the expectations as a predictor of the IPI. The multivariate time series approach produced short-term predictions for IPI for September, October and November of 2024 (Table 1) and the values are in line with the expected values of the entire time-series.

Table 1: Comparison between real and forecasts for IPI using the cointegration tie, Italy, Sep-Nov 2024

	Sep.2024	***Oct.2024***	***Nov.2024***
IPI real	94.3	94.2	94.2
IPI forecasts	93.8	94.7	94.8

The proposed approach has been used to detect short-term movements for the Industrial Production Index in order to anticipate possible outliers in the time series due to possible crisis. The cointegration-based approach confirms the existence of a relationship between the two time-series, producing reliable estimates of the IPI three months in advance. The values obtained were compared with the actual IPI values in order to verify the robustness of the proposed approach. In this application, the values obtained are in line with the actual values, justifying this approach in standard situations. The effectiveness of this approach needs to be verified in the event of an economic crisis, justifying its use as an anticipatory tool.

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Spatial DID for interdependent outcomes: GDP, unemployment, and the Italian NUTS 3

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Abstract A system of spatial Difference-in-Differences equations is developed to estimate the interdependent effect(s) of economic growth and unemployment. This approach allows for identifying the policy effect on an outcome of interest, its effect on a different but strictly related outcome, and potential spillovers on the same or other outcomes. Empirical application focuses on the Italian provinces and the European Commission's Regional Policy 2007-2013.

Key words: diff-in-diff, italian provinces, cohesion policy

1 Introduction

Economic disparities within the European Union (EU) represent a persistent challenge, endangering long-term economic and social cohesion. Aiming to reduce regional disparities and achieve inclusive growth across the EU, the Regional Policy (Cohesion Policy) allocated substantial resources in 2007-2013, approximately 352 billion Euro in 2014-2020, and, to date, nearly 1/3 of the EU total budget.

[3] indicates that, although convergence is occurring, there are persistent challenges: *i*) disparities between large metropolitan areas and other regions, *ii*) regions stuck in a "development trap" [5], *iii*) policies effectiveness vs. physical and cultural contexts where they are implemented, *iv*) potential spillover effects of tailored policies on neighboring areas. In such a context, simultaneous relationships between the economic and social goals of the policies are important too, as well as the simultaneity of policy goals and the presence of spatial phenomena.

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The literature analyzed the existence of spatial transmissions and spillover effects in policy evaluation [2, 1, 6]. However, to the best of our knowledge, no work has considered estimating a policy impact on target variables characterized by simultaneous interdependence, such as economic growth and unemployment.

We propose a difference-in-differences (DID) estimation approach considering a two equations system, accounting for spatial phenomena and for the interdependence of GDP growth and unemployment rate. We introduce the cross-average treatment effect (C-ATE), capturing the impact of a treatment targeting one outcome variable over another related outcome, whether the treatment occurs within the same area, i.e. "directly" (C-ADTE) or in neighboring territories, i.e. "indirectly" (C-AITE). The Italian provinces are the target; the EU Cohesion Policy 2007-2013 with 2014 and 2015 as follow-ups is the "policy treatment". From [4], NUTS 3 are (alternatively) defined as treated whether they show a value of funds equal or greater than the average level, the 1^{st}, 2^{nd}, and 3^{rd} quartiles of the distribution of funds.

2 Methodology

Let $i = 1,\dots,N$ be the units observed over $t \in [0,1]$ time periods. $D_i = 1$ defines treated units; $D_i = 0$ untreated ones. The standard estimator proposed for the treatment effect on Y, in regression form, is a linear combination of unit fixed effects, time fixed effects, the treatment variable indicator and the error term. In such a context, [1] propose (dropping the subscript i) what follows:

$$\begin{aligned} y_t &= \alpha\iota_n + \beta X_t + \delta D + \tau T_t + \zeta(I + \psi W)D \circ T_t + \varepsilon_t \\ &= \alpha\iota_n + \beta X_t + \delta D + \tau T_t + \zeta D \circ T_t + \rho W D \circ T_t + \varepsilon_t \\ &= \alpha\iota_n + \beta X_t + \delta D + \tau T_t + \zeta D \circ T_t + \rho D_w \circ T_t + \varepsilon_t, \end{aligned} \tag{1}$$

where $y_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$ is a $n \times 1$ vector of n outcomes; ι_n is a $n \times 1$ vector of 1; the $n \times 1$ vector D is the treatment indicator variable; the time indicator variable ($n \times 1$ vector) T_t is equal to 0 in the treatment period, 1 in the post-treatment instant. The term $(I + \psi W)D = D + \psi WD = D + \psi D_w$ represents the overall interactions of outcomes, with ψWD that is the outcomes spatial interaction counterpart. The final treatment effect is the sum of the effect $\zeta D \circ T_t$ related to a specific area of interest, and a quote ρ of the treatment effects observed in neighboring areas, i.e. $\zeta\,\psi WD \circ T_t = \rho WD \circ T_t$ ($\circ$ is the Hadamard product). The residual term ε_t is assumed i.i.d. with location and scale parameters $(0_{n\times 1}, \sigma^2_\varepsilon I_n)$, such that $\mathrm{E}[\varepsilon_t | X_t, D, T_t] = 0$. Covariates may be included as per the $n \times k$ matrix X_t.

Willing to account for potential interdependence of the outcomes, in a certain area and in its neighborhood, we propose a model where a system of DID equations is characterized by spatial correlation in the response to treatment, as

$$Z_t = \boldsymbol{\Gamma} Z_t + \boldsymbol{\alpha} + \boldsymbol{B} vec(X_t) + \boldsymbol{\delta} \boldsymbol{D} + \boldsymbol{\tau} \boldsymbol{T}_t + \boldsymbol{\zeta}(\boldsymbol{D} \circ \boldsymbol{T}_t) + \boldsymbol{\zeta} \circ \boldsymbol{\Psi}(\boldsymbol{W}(\boldsymbol{D} \circ \boldsymbol{T}_t)) + \boldsymbol{\varepsilon}_t. \quad (2)$$

Here, $t = 1,2$; $Z_t = (z'_{1t}, \ldots, z'_{mt})'$ is a $nm \times 1$ vector collecting m different outcomes for each of the n areas. $\boldsymbol{\Gamma} Z_t$ collects possible simultaneity effects among the m outcomes, with $\boldsymbol{\Gamma} = (\Gamma \otimes I_n)$, where Γ is a matrix of $m(m-1)$ off-diagonal free parameters and zeros on the main diagonal. $\boldsymbol{\alpha} = (\alpha \otimes \iota_n)$ is the vector of intercepts $\alpha_1, \ldots, \alpha_m$. Covariates X_t, for simplicity, are assumed to be the same across all equations. The associated parameter matrix, $\boldsymbol{B} = (B \otimes I_n)$ is of dimension $nm \times nk$. The treatment indicator variable is $\boldsymbol{D} = (D'_1, \ldots, D'_m)'$, consisting of vectorized m distinct treatment indicators which remain constant over time, with associated parameters $\boldsymbol{\delta}$ of dimension $nm \times nm$, such that each m outcome variable can be affected by all treatments. The matrix $\boldsymbol{\delta} = (\delta \otimes I_N)$ collects outcome-specific treatment parameters on the main diagonal, while off-diagonal elements refer to cross-outcome treatments. For a given i-th area that is untreated, $\sum_{i_m=1}^{m} D_{i_m,i} = 0$. If the i-th area is treated, $\sum_{i_m=1}^{m} D_{i_m,i} > 0$, with the sum indicating the number of outcomes in the i-th area affected by the treatment, for $i_m = 1, \ldots, m$. The effect of time is given by the term $\boldsymbol{\tau} \boldsymbol{T}_t = diag(\tau \otimes \iota_n) \boldsymbol{T}_t$, where $\boldsymbol{T}_t = (T_t \otimes \iota_{mn})$, $T_t \in [0,1]$ is a scalar detecting the temporal instants, and $\tau = (\tau_1, \ldots, \tau_m)'$ is the associated $m \times 1$ parameter vector entering as diagonal matrix. The treatment effect is collected by $\boldsymbol{\zeta}(\boldsymbol{D} \circ \boldsymbol{T}_t) = (\zeta \otimes I_n)(\boldsymbol{D} \circ \boldsymbol{T}_t)$, where, for each output, the matrix ζ collects by row the response coefficients to the m treatments. To allow the possibility that outcomes are influenced by treatment effects of neighboring areas, the term $\boldsymbol{\zeta} \circ \boldsymbol{\Psi}(\boldsymbol{W}(\boldsymbol{D} \circ \boldsymbol{T}))$ is included in the model (it corresponds to $\boldsymbol{\rho}(\boldsymbol{W}(\boldsymbol{D} \circ \boldsymbol{T})) = \boldsymbol{\rho}(\boldsymbol{D}_W \circ \boldsymbol{T}_t)$ in the vein of [1]), where the $\boldsymbol{\Psi} = (\Psi \otimes I_n)$ matrix collects m^2 free parameters capturing the spatial effects across neighborhoods in Ψ, the $m \times m$ matrix of spatial coefficients (e.g., for $m = 2$, $vec(\Psi) = (\psi_1, \psi_{21}, \psi_{12}, \psi_2)'$).

3 Application and results

The system of spatial DID equations for $t = 1,2$ is given by

$$\begin{aligned} y_t = \alpha_y + \gamma_y \dot{u}_t + X\beta_y + \delta_y D_y + \delta_u^c D_u + \tau_y T_t + \\ \zeta_y(D_y \circ T_t) + \zeta_u^c(D_u \circ T_t) + \psi_y W_a \zeta_y(D_y \circ T_t) + \psi_{yu} W_b \zeta_u^c(D_u \circ T_t) + \varepsilon_{yt} \\ u_t = \alpha_u + \gamma_u \dot{y}_t + X\beta_u + \delta_u D_u + \delta_y^c D_y + \tau_u T_t + \\ \zeta_y^c(D_y \circ T_t) + \zeta_u(D_u \circ T_t) + \psi_{uy} W_b \zeta_y^c(D_y \circ T_t) + \psi_u W_a \zeta_u(D_u \circ T_t) + \varepsilon_{ut}, \end{aligned} \quad (3)$$

with y_t and u_t representing GDP growth and unemployment rate at time t.

The estimated models for policy evaluation with the two follow-up years 2014 and 2015 provide results reported in Table 1.

The estimated four different average treatment effects (ADTE, AITE, cross equations ADTE and AITE, i.e. C-ADTE and C-AITE), are depicted in Table 2.

Table 1 Estimation results. *: p-value ≤ 0.10; **: p-value ≤ 0.05; ***: p-value ≤ 0.01.

	Follow-up: 2014				Follow-up: 2015			
Equation	y		u		y		u	
y	-		-1.307	***	-		-0.683	*
u	-0.145	***	-		0.058		-	
Const	-0.020	***	0.210	***	-0.027	***	0.209	***
D_y (status)	-0.002		0.010	*	-0.003		0.010	**
D_u (status)	-0.003		0.002		-0.003		0.002	
T (trend)	0.009		-0.047	***	0.040	***	-0.047	***
$D_y \circ T$	0.004		0.000		0.007		-0.007	
$D_u \circ T$	0.011	**	0.006		0.006		0.004	
X_{mun}	0.108	***	-0.590	***	0.107	***	-0.596	***
X_{prov}	0.011		-0.013		0.028	*	0.016	
$W(D_y \circ T)$	0.000		0.136	***	0.002		0.129	***
$W(D_u \quad T)$	-0.003		0.030	**	-0.041	***	0.020	*

Table 2 Average Treatment Effects. *: p-value ≤ 0.10; **: p-value ≤ 0.05; ***: p-value ≤ 0.01.

		Follow-up: 2014				Follow-up: 2015			
Equation		y		u		y		u	
Mean	ADTE	0.0035		0.0059		0.0074	*	0.0037	
	AITE	0.0000		0.0002		0.0000		0.0001	
	C-ADTE	0.0106	***	0.0003		0.0058	***	-0.0063	***
	C-AITE	0.0000		0.0004	*	-0.0002		0.0008	*
1^{st} quartile	ADTE	0.0101	*	0.0053		0.0111	**	0.0058	
	AITE	-0.0001	*	-0.0003	**	0.0000		-0.0003	**
	C-ADTE	0.0069	***	0.0008		-0.0039	***	-0.0121	***
	C-AITE	0.0000		0.0003	***	0.0001		0.0004	***
2^{nd} quartile	ADTE	0.0085	*	0.0051		0.0097	**	0.0020	
	AITE	0.0000		0.0000		0.0000		0.0000	
	C-ADTE	0.0049	***	0.0027	*	0.0005	***	-0.0063	***
	C-AITE	0.0000		0.0003	**	-0.0001		0.0004	***
3^{rd} quartile	ADTE	-0.0020		0.0060		0.0071		-0.0003	
	AITE	0.0000		0.0003	**	0.0001		0.0000	
	C-ADTE	0.0082	***	-0.0060	***	0.0008	***	-0.0132	***
	C-AITE	-0.0002	*	-0.0002		0.0000		0.0006	***

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Territorial Profiling and Latent Segmentation of Italian Regions Based on the R-GEI Index Using Self-Organising Maps

Angela Maria D'Uggento, Enrico Di Bella, Sara Preti, Ernesto Toma and Annalisa Bellino

Abstract This study employs Self-Organising Maps (SOM) to analyse gender equality sub-domain structures across 20 Italian regions, using the six indices from the EIGE framework. The codebook vectors were clustered with K-Means to identify macro-regional profiles. The SOM identified four latent territorial typologies: socio-economic and welfare-balanced leaders, time-health optimised territories, welfare-supported but materially constrained regions, and structural mid-equilibrium areas. The results show that multidimensional similarity implies shared trade-off configurations among gender equality domains. SOM is robust for small territorial matrices where topology preservation and interpretability are priorities, providing policy-relevant spatial insights through an unsupervised, data-driven approach.

Key words: Self-Organizing Maps, Regional Gender Equality Index (R-GEI), Regional Profiling, Latent Territorial Clustering.

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This research is funded by Regione Puglia with the Project Navigare nella parità. Prot. N.0456053/2024, Bari 20/09/2024

1 Introduction

The analysis of gender inequalities has traditionally relied on the Gender Equality Index, developed by the European Institute for Gender Equality (EIGE) [2]. This composite index measures gender equality in the European Union across six key socio-economic domains: Work, Money, Knowledge, Health, Time and Power. Based on 31 indicators and a scale from 1 to 100, it tracks progress in gender equality since 2005 and highlights areas needing further policy intervention. Recognised by the EU Gender Equality Strategy 2020–2025 as a key benchmark, the index has been published annually since 2019 and is accompanied by thematic analyses and country-specific factsheets. Recent research [1] developed the index at the regional level, naming it R-GEI, while international institutions [3] have highlighted the need for multidimensional tools to assess progress towards equality. Spatial inequality profiling has typically relied on partition-based clustering or composite-index ranking. However, when territorial units are represented by correlated sub-domain scores, topological neural networks such as Self-Organising Maps [6; 7] preserve multidimensional similarity structures in two-dimensional projections [9; 4]. This study applies SOM neural networks to the R-GEI to identify latent territorial typologies through domain trade-off patterns, rather than through supervised prediction or purely metric-based segmentation. The macro-clusters were calculated using K-Means on the weights of the neurons, resulting in four groups of macro-areas composed of regions with similar average profiles. The paper is organised into four sections. After a brief introduction, the second section describes the methodology of SOM, the third presents the results, and the fourth provides a brief conclusion.

2 Methodology

SOMs are competitive neural networks that learn a two-dimensional topology preserving multidimensional similarity. A SOM was applied to a 20 × 6 Italian regional matrix based on R-GEI sub-domain indices. All data, collected mainly from official sources, such as ISTAT, were standardised using z-score normalisation. A 5 × 5 Kohonen grid (25 neurons), chosen to balance interpretability given the limited number of observational units, was randomly initialised and trained for 3,000 iterations using competitive learning [6; 7]. For each input vector, the Best Matching Unit (BMU) was identified by minimising Euclidean distance in weight space, followed by Gaussian neighbourhood-based weight adaptation [9]. The U-Matrix was inspected to detect local weight discontinuities and cluster borders, capturing gradients rather than variance-minimising partitions [8]. Codebook vectors were clustered via K-Means (k = 4), and each region inherited its BMU neuron's cluster label. The analysis followed a fully unsupervised, topology-preserving territorial segmentation approach [5; 8]. This property is especially relevant for territorial profiling where gradients between regions are often more informative than hard partitions.

3 Results

The trained SOM organised Italian regions into four macro-clusters, which emerged from codebook vector segmentation as shown in Table 1 and detailed below.

Table 1. Mean sub-domain indices by SOM cluster

Cluster	Work	Money	Knowledge	Health	Time	Power
1	76.78	63.80	69.23	80.67	82.03	32.53
2	75.49	61.65	60.32	74.02	73.47	28.16
3	79.83	73.05	62.84	79.77	82.05	33.83
4	73.14	59.38	54.30	79.01	75.95	28.39

Cluster 1 - Balanced structural convergence (Lazio, Trentino Alto Adige, Umbria): compact, internally cohesive and structurally balanced across all EIGE sub-domains, without extreme peaks. The SOM topology suggests these regions share a harmonised structural position in codebook space, reflecting comparable scores in labour participation, material conditions, and temporal-health dimensions, where equality-related sub-domains co-evolve in a mutually compensating balance. This indicates a resilient but non-specialised latent model of regional gender-equality dynamics.

Cluster 2 - Mid-range composite equilibrium (Abruzzo, Basilicata, Campania, Liguria, Molise, Piemonte, Puglia, Toscana): this is the largest and most heterogeneous macro-segment, but with a consistent centroid-proximal organisation within the SOM grid. Regions in this cluster exhibit scores that cluster around the national mid-upper average. The inclusion of both southern and northern regions, along with territory-specific outliers (e.g., Liguria, Piemonte, Toscana), indicates that this group shares a moderate structural signature across domains, particularly balancing Work, Money, and Health indicators, but showing comparatively weaker cohesion in Knowledge and Power domains.

Cluster 3-Socio-economic and top-performance core (Emilia Romagna, Friuli Venezia Giulia, Lombardia, Marche, Veneto): the most topologically distinct and interpretable group, positioned on the SOM grid in mutually adjacent or low-distance neurons, forming a competitive codebook basin. These regions share a high-performance composite profile, combining the strongest mean values in Work and Money (labour participation and material resources), Time and Health (temporal conciliation and welfare-related conditions), and the highest representation in Power among clusters. This defines a structural excellence model where economic capital, welfare capacity, and decision-domain representation co-occur, generating a high-amplitude equality regime. The cluster composition is geographically coherent (predominantly northern/industrial regions), and the interpretation emphasises neural-learned territorial similarity based on joint domain strength.

Cluster 4 - Welfare-similar but resource-constrained gradient group (Calabria, Sardegna, Sicilia, Valle d'Aosta): this cluster groups territories that the SOM has positioned as mutually similar in codebook space due to shared configurations of domain trade-offs, particularly relatively strong or aligned Health and Time indices,

but lower or more compressed scores in Money and Knowledge. This macro-segment captures southern regions along with a northern, low-population autonomous outlier (Valle d'Aosta), suggesting a latent similarity regime defined by constrained material and human-capital dimensions. This confirms that SOM clusters may represent regions distant from top-performing basins but internally proximal due to comparable structural limitations and domain gradients, rather than absolute negative performance labels.

4 Discussion and conclusion

The SOM enabled us to identify a topology-preserving two-dimensional typology of Italian regions based on six EIGE gender-equality sub-domains. The neural projection revealed four latent profiles shaped by multidimensional similarity gradients across socio-economic capital (Work, Money, Power), welfare and conciliation dimensions (Health, Time), and human capital (Knowledge). Consistent with previous research on topology-preserving neural clustering for small territorial matrices, the SOM demonstrates strong interpretability, internal topological coherence, and robustness with limited observational units. Notably, regional proximity on the map reflects shared multidimensional trade-off configurations rather than supervised performance rankings or externally imposed partitions. The results underscore the analytical value of SOM for spatial inequality profiling, gradient-based regional classification, and evidence-driven, policy-relevant segmentation of complex sub-domain matrices.

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The Efficiency of European Welfare Systems: A Canonical Correlation Analysis of Senior Well-being and Social Protection.

Marco Arlotti, Mariateresa Ciommi, Francesca Mariani and Maria Cristina Recchioni

Abstract This study evaluates the efficiency of European welfare systems in promoting senior well-being across 30 countries from 2013 to 2020. Using Canonical Correlation Analysis, we developed two composite indices to measure the relationship between welfare inputs (expenditure and demographics) and quality-of-life outputs (health and economic security).

Key words: CCA, Composite indicators, older population

1 Introduction

To investigate the nexus between social protection and senior well-being, this study employs Canonical Correlation Analysis (CCA) [3], a method particularly suited for analyzing the older population as it treats well-being as a multidimensional phenomenon [1]. This dual-set configuration allows for the identification of optimal linear combinations that maximize the correlation between what a state invests in

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terms of welfare inputs and the actual quality of life experienced by its older citizens.

2 Data

The empirical analysis is based on a longitudinal dataset comprising 30 European countries observed over the period 2013-2020. The data, primarily sourced from Eurostat, have been harmonized to ensure cross-national comparability. To evaluate the efficiency of national welfare systems, the variables ([2]) are organized into two functional sets representing the inputs and outputs of the social protection mechanism. The first set, the Welfare Machine (Set X), characterizes the structural effort and the demographic challenges faced by each country: *i)* Social Protection Expenditure on Old Age (*SPEOA*, `spr_exp_func`): Public expenditure on old-age benefits expressed as a percentage of GDP. It serves as a proxy for the financial intensity of the welfare state. *ii)* Old-age Dependency Ratio (*OADR*, `tps00198`): The ratio of the number of older people (aged 65 and over) to the working-age population. This variable represents the demographic pressure on the system. *iii)* Pension Share (*PS*, `spr_pns_ben`): The weight of old-age pensions relative to total social benefits, indicating the policy focus on monetary transfers.

The second set, the Output Set: Realized Well-being (Set Y), it measures the multidimensional outcomes of the welfare system in terms of quality of life for older people: *i)* Healthy Life Years at 65 (*HLY*65, `hlth_hlye`): The number of remaining years that a person aged 65 is expected to live without disability. It is the primary indicator of physical well-being. *ii)* At-risk-of-poverty rate (*ARPR*, `tespm090`): The percentage of individuals aged 65 and over with a disposable income below the poverty threshold, measuring the effectiveness of economic protection. *iii)* Relative Median Income Ratio (*RMIR*, `ilc_pnp2`): The ratio of the median income of persons aged 65+ to the median income of those under 65, reflecting intergenerational equity. *iv)* Work Intensity (*WI*, `lfsa_ergan`): A measure of labor market integration or active aging, indicating the degree of social and economic participation of the older people.

This selection of indicators allows for a comprehensive assessment of how national welfare systems transform structural and financial resources into tangible social well-being, especially under the exogenous shock of the 2020 pandemic.

3 Results and Discussion

The statistical analysis performed through *CCA* reveals a robust and significant relationship between the welfare inputs (Set X) and the well-being outputs (Set Y) for the older population across the 30 European countries studied.

The model demonstrates high reliability, as evidenced by the *Wilks' Lambda* test. All three canonical dimensions are statistically significant ($p < 0.001$), confirming that the well-being of older people is a multidimensional phenomenon.

The canonical loadings provide a detailed map of the "mechanisms" governing European welfare systems across the identified dimensions. While the first dimension is the most influential, explaining 43.6% of the variance in the Output set, the integration of all three significant dimensions allows for a truly multidimensional assessment.

- System Inputs (X): The primary driver of the "Welfare Machine" is *SPEOA*, with a dominant loading of 0.907. The *OADR* carries a negative loading of -0.401, confirming that high demographic pressure represents a structural burden that requires significant fiscal effort to be mitigated. The *PS Pension Share* shows a marginal loading of -0.073 in this first dimension, suggesting that the total volume of spending is more decisive than the specific weight of pensions alone.
- Well-being Outcomes (Y): The effectiveness of these inputs is most visible in the sharp reduction of the *ARPR* (loading -0.893) and the promotion of physical health through *HLY*65 (loading 0.808). Economic integration also plays a role, with the *RMIR* (0.459) and *WI* (0.288) contributing to the overall quality-of-life construct.

The subsequent dimensions capture secondary but essential facets of the system. For instance, the second dimension is strongly characterized by the demographic challenge (*Old-age Dependency Ratio* at 0.887), while the third dimension highlights the policy orientation toward monetary transfers (*Pension Share* at 0.799).

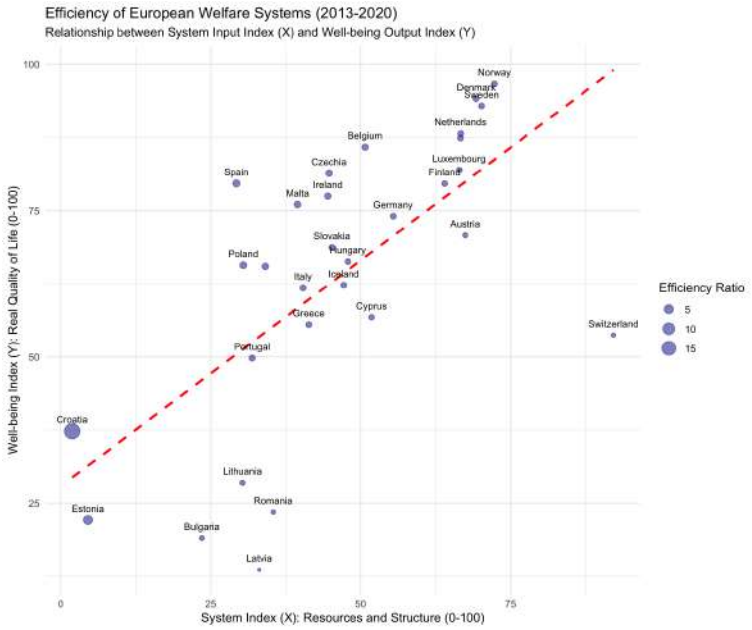
3.1 Construction of the Composite Welfare and Well-being Indices

To account for all canonical dimension, we propose the construction of two composite indicators, the Welfare System Index (X) and the Older people's Well-being Index (Y), following a three-step robust aggregation methodology. First, canonical scores are extracted for each country and aligned in terms of polarity to ensure that higher values consistently represent better performance across all dimensions. Second, the two indicators are obtained as a weighted arithmetic mean of the canonical dimensions, which are constructed by combining the original variables using weights that measure the proportion of variance explained by each canonical dimension.

Finally, a Min-Max normalization is applied to the resulting scores, with 0 and 100 denoting the worst performer and the best performer, respectively.

While the indices were calculated for each year in the `2013-2020` panel to observe temporal trends, the final rankings presented in the study are based on the arithmetic mean of these annual scores (Figure 1). This averaging process smooths out short-term fluctuations and captures the structural performance of each national welfare system over the analyzed period.

The calculated Efficiency Index (Y/X) allows for a comparative evaluation of how effectively countries transform their structural resources into quality of life.



The yearly analysis reveals significant disparities in efficiency: while Nordic countries lead in absolute well-being, Mediterranean and Central-Eastern models demonstrate higher efficiency in resource transformation. Moreover, this longitudinal analysis highlights the profound impact of the COVID-19 pandemic, uncovering structural vulnerabilities in systems with high rigidity during the final year of the observed period. The analysis proves that higher spending does not automatically guarantee higher well-being. For instance, Spain stands out with an efficiency score of 2.72; despite a relatively low system input, it achieves a well-being output comparable to much wealthier nations. Conversely, Switzerland exhibits the lowest efficiency (0.58), suggesting a "diminishing returns" effect or a systemic misalignment between expenditure and actual health outcomes.

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The Environmental Footprint of the Final Demand in Italy: a Supply-Use Table Approach of Economic Assessment

Caterina Marini and Vittorio Nicolardi

Abstract It is well known that household consumption is one of the most important factors that affects the environmental stability and the economic decisional process of all the advanced economies. And, in the last decade, the environmental unsustainability of production activity to meet the household consumption need is recognised as one of the most affecting causes of general pollution. This paper is focused on the socioeconomic and environmental impact that the household consumption categories experience in Italy and is a first attempt to develop a unique social, economic and environmental model embracing all categories of consumption. Supply-Use Tables merged with the Social, Economic and Environmental Matrices, as published by ISTAT, and the Economic Input-Output model are used.

Key words: Environmental footprint, Household consumption, Leontief's model

1 Introduction

The human responsibility on the escalation of the climate change is already a certainty and worldwide all countries are trying to promote political strategies that can induce a changing gear in the population behaviours and economic activities to lessen the effects of the problem. Measurement of the environmental footprint of human activity and the socioeconomic consequences of the rapid change we are experiencing is a crucial aspect of the problem and, in this sense, there is still a lot of work to undertake and carry out. A pioneer in the formulation of the environmental problems and correlated economic effects was Wassily Leontief. In his work [2], he laid the base of the input/output model to also incorporate the undesirable negative externalities of pollution into the input-output framework to quantify how the mod-

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ern technology and the uncontrolled economic growth can affect the environment. His method is still a valid and robust methodological tool. In the last decades, it has been recognised that the production activity for household consumption, both commodities and services, are environmentally unsustainable. In literature, many studies differently investigate on some categories of consumption and their sustainability, and not few studies based their research on a variety of scientific perspectives that highlight many aspects of the ecological footprint of consumption and some of them yield their findings through the Symmetric Input-Output matrices, methodologically and/or empirically (Turner et all [3]; Wiedmann et al. [4]). This work aims to evaluate the effects of policymaker decisions on the amount of final demand and their direct consequences on the increase of production and indirect costs in terms of pollution. Specifically, an increase in the final demand of a particular typology of goods/services causes an increase in production that involves not only the direct branch involved in the production process but indirectly also all or the great part of branches that provide goods/services consumed as inputs by the same production process, which are part of another production process generating a cascade effect. In this sense, to achieve our objectives we have decided to apply the Leontief's Final Demand – Production Model, also in terms of pollution. In particular, we have decided to apply the model based on the Supply-Use Tables (SUTs) that allows to evaluate the direct-undirect effects of the increase in the final demand for a well-defined typology of goods/services on the production of branches in a productive economy of a country[1]. Kucukvar et al. [1] were the first to evaluate on the macro-level the socio-economic and environmental impacts of the food consumption categories in the US by using the SUTs model. We use, instead, the SUTs model to analyse the direct effects of the increase in the final demand of all typologies of goods/services on the production of the several productive branches and, indirectly, on the polluting emissions caused by the corresponding increased production.

2 The Method and Data

The Leontief's Final Demand – Production Model we applied needs the following matrices:

- the matrix $\mathbf{B}$ of the input coefficient of the Use Table (UT), given by: $\mathbf{B} = \mathbf{X^I}\, diag(\underline{\mathrm{p}})^{-\mathbf{1}}$, where $\mathbf{X^I}$ is the UT matrix of domestic intermediates (product by branch) and $\mathbf{p}$ is the vector of branch output by NACE;
- the matrix $\mathbf{D}$ of the market shares matrix, given by $\mathbf{D} = \mathbf{V}\, diag(\mathbf{q})^{-\mathbf{1}}$, where $\mathbf{V}$ is the make matrix branch by product that is the transpose of the Supply Matrix (ST) (product by branch), and $\mathbf{q}$ is the vector of the total output (domestic and imported) by CPA.

The estimation of the domestic production $\hat{\mathbf{p}}$ by NACE for a given final demand vector f is possible through the Leontief's Input-Output Model as follows:
$\hat{\mathbf{p}} = \left[\mathbf{D}(\mathbf{1} - \mathbf{B}\,\mathbf{D})^{-\mathbf{1}}\right] \mathbf{f} = \bar{\mathbf{A}}\,\mathbf{f}$, where $\bar{\mathbf{A}}$ is the *Leontief inverse*.

[1] The symmetric Input-Output model, instead, allows to evaluate the direct-undirect effects of the increase in the final demand of a branch on the production activity of all the other branches in the economy.

Finally, the total environmental impact vector $\boldsymbol{\eta}$ of the production $\hat{\mathbf{p}}$ is worked out through the Hadamard product involving $\mathbf{E}$ that is the matrix of the amounts of the direct environmental impacts per one euro of output for each NACE division: $\eta = \mathbf{E} \circ \hat{\mathbf{p}} = \mathbf{diag}(\hat{\mathbf{p}})\,\mathbf{E}$. Each component of $\mathbf{E}$ is calculated by dividing the total direct sectorial environmental impact by the total economic sectorial output.

The sole data source used for this preliminary analysis is the National Institute of Statistics (ISTAT). Regarding the Leontief's Model, we used the 2021 SUTs, the last available on ISTAT data warehouse, disaggregated in 63 CPA divisions and 63 production branches, which are homogeneous with the NACE Rev2 divisions. Regarding the atmospheric emissions of pollutants yielded by the production process, we used the Air Emission Accounts (AEAs) for the period 2008 – 2022 disaggregated in 88 NACE Rev2 divisions. However, we used atmospheric emission data in 2021 to homogenise data with the 2021 SUTs. As expected, it was necessary to work separately on both SUTs and AEAs to make them homogeneous within their own contents and between them.

3 Outcomes and Conclusions

We are investigating how the increase of the total final demand for each CPA division affects the increase of pollutants because of the increase of production to satisfy the same final demand. First, for the whole economy and each NACE division we worked out the change of production at basic prices caused by the change of the final demand in each CPA goods/services. Therefore, we simulated a generic increase of 10% in final demand of each CPA division[2] and, afterwards, we proceeded with the evaluation of the change in Atmospheric Polluting Emissions (APE) caused by the increase in production. Therefore, first we worked out the quantity of emissions per each atmospheric pollutant per each euro of output of each CPA division, and afterwards we estimated the change in polluting emissions per each increase of production caused by the increase in the final demand per each CPA good/service. In this way, we can work out the analysis for each CPA good/service in terms of atmospheric polluting emissions. Furthermore, we calculated also the Economic Impact Multiplier (EIM) that specifies how every euro of the final demand increase in the corresponding CPA division causes the increase (in euros) in the production at basic prices of the whole production process. Table 1 shows an exemplyfing case study. As we can see, although the CPA RD division causes the largest increase in production of the whole economy, that is not the most polluting in terms of CO2. In fact, in this sense, the most polluting CPA division is the CPA RF with almost 2.5 million tons of CO2. A disaggregated analysis of the atmospheric pollutant emissions per each pollutant corresponding to each CPA division shows the pollutants we face caused by a 10% increase of final demand. An exemplyfing case study based on CPA RD shows that a 10% increase in final demand causes a significant increase in Greenhouse (GRHO) and, secondarily, Carbon dioxide without biomass used as fuel (CO2). The Leontief's Model can also be applied to estimate other correlated

[2] All values and outcomes not reported in this paper are available under request.

aspects with the environmeltal issue. For istance, we worked out a last exemplyfing outcome that merges the GRHO emissions and the level of employment per CPA. As we can see in Table 2, R19 and RD are the most polluting CPA products in terms of FTE employment. The method we defined is new in the academic literature and the outcomes are original in the analysis of the effects that the final demand produces on the ecological equilibria. In the end, we yielded a database that is a three-dimensional OLAP cube CPA x NACE x Pollutants.We can affirm that the Leontief's Final Demand-Production Model based on SUTs provides a great opportunity to measure the impact of the final demand on the environmental footprint. The analysis can be disaggregated at any level based on the analytical targets.

Table 1 Estimated Change in Atmospheric Emissions for a 10% increase in final demand per CPA Products arranges by $\Delta\hat{Q}_{Poll}$. Pollutant: CO2 - carbon dioxide (without biomass used as fuel). **p** in Mln of €, Q_{Poll} in tons. Economic Impact Multiplier per CPA

CPA	$\Delta\hat{p}$	$\Delta\hat{Q}_{Poll}$	$\Delta\%\hat{Q}_{Poll}$	EIM
RF - Constructions and construction works	36,144	2,427,466	1	2.155
RL - Real estate services	24,683	1,657,734	0.68	1.221
R10_12 - Food, beverages and tobacco products	23,364	1,569,149	0.65	1.922
R86 - Human health services	23,149	1,554,709	0.64	1.618
R47 - Retail trade services, except of motor vehicles and motorcycles	20,628	1,385,396	0.57	1.704

The Table reports the first five positions in the list

Table 2 Mean Emissions Intensity of Employment per CPA. Tons per thousand of Full-Time Equivalent employee.

CPA	GRHO
R19 - Coke and refined petroleum products	692,233.8
RD - Electricity, gas, steam and air conditioning	600,532.9
R51 - Air transport services	398,838.7
R50 - Water transport services	338,968.7
RB - Mining and quarrying	219,106.2

The Table reports the first five positions in the list

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The future of healthcare: a longitudinal study on Generation Z's impact on clinical and organizational paradigms

Erika Grammatica

Abstract The FutureS Study, by B-ASC and IPSOS Doxa, explores the transformation of Italian healthcare over the next 5–7 years, focusing on the Generation Z transition and systemic challenges. Key drivers include rising health inequalities due to poverty and a 18% increase in GP patient loads since 2003, with 2035 projections showing a demographic shift toward elderly care. Using desk analysis and text mining of a June 2025 survey among industry managers, the study identifies latent trends and organizational risks. This evidence-based framework sets the stage for a Delphi phase involving specialists to redefine clinical and sustainability paradigms in response to population aging and evolving professional needs**.**

Key words: healthcare systems, generational transition, population aging, desk analysis, text mining

1 Introduction

The Italian healthcare system is undergoing a transformative crisis, driven by the convergence of demographic shocks and growing socioeconomic barriers. Data show an 18% increase in the care burden for general practitioners (GPs) in twenty years, from an average of 1,099 patients (2003) to 1,301 (2022). This scenario is exacerbated by growing absolute poverty, which acts as a barrier to access, fueling regional inequalities between North and South and leading to a progressive forgoing of care. By 2035, the peak care burden for patients is expected to shift toward the 60-70 age group, necessitating new organizational paradigms.

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2 Objective

The study aims to explore how the new generation of professionals is transforming clinical, relational, and organizational paradigms, identifying the exact coordinates of upcoming changes within the NHS and the pharmaceutical industry. By mapping who the new key stakeholders are, the research establishes how pharmaceutical companies should strategically position themselves to thrive in these emerging future scenarios.

3 Methods

The research adopts a multidimensional approach coordinated by B-ASC and IPSOS Doxa. The first phase involved a demographic and economic desk analysis to establish a framework of evidence.

Subsequently, in June 2025, a survey was conducted among a panel of healthcare managers. Text Mining techniques, including frequency analysis (Word Clouds) and bi-grams, were used for qualitative data analysis to identify recurring semantic patterns and latent themes [1,2,3].

This methodological path will be finalized with a Delphi study, involving physicians and specialists to validate the future scenarios identified in the previous stages.

4 Results

The desk analysis results highlight unprecedented structural pressure: the average number of patients per GP rose by 18%, from 1,099 (2003) to 1,301 (2022), with a worrying acceleration in the last six years (+10%). Demographic projections for 2035 show a radical transformation of the age pyramid: while in 2014 the peak of patients was concentrated between 40 and 50 years old, by 2035 healthcare demand will be dominated by the 60–70 age group (Fig. 1).

In parallel, text mining analyses of healthcare managers reveal that while Telemedicine and AI are seen as key opportunities, "staff shortages" and "bureaucratization" are perceived as critical obstacles that risk compromising care quality and system sustainability (Fig. 2).

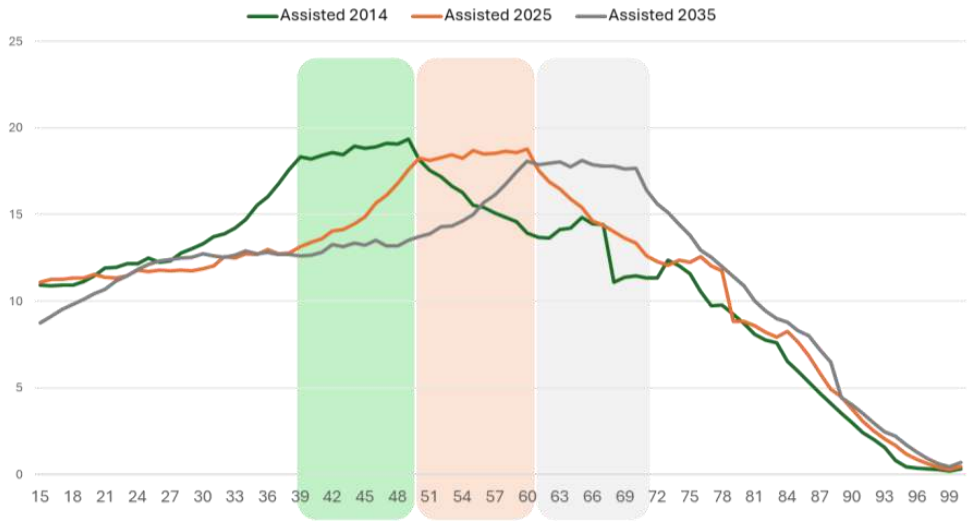

Figure 1: *Scenario - number of patients per general practitioner, broken down by age (base: 1,000 patients)*

***Source**: ISTAT data processing*

Figure 2: *"Thinking about the Italian healthcare system, what changes do you expect to see in the next 5-7 years?"*

5 Conclusion

In conclusion, the survival of the National Health Service depends on a two-dimensional transition: technological and human. It is imperative to automate bureaucratic processes to return "care time" to the doctor-patient relationship.

New organizational paradigms must integrate the flexibility demanded by new generations of doctors with the needs of an increasingly fragile and aging population.

Through synergetic coordination between the public and private sectors, will it be possible to mitigate social inequalities and ensure that innovation becomes a tool for equity rather than a further factor of exclusion.

Acknowledgements: The research team at B-ASC – University of Milan-Bicocca is made up of: Erika Grammatica; Paolo Mariani; Andrea Marletta; Daniele Pirotta and Mariangela Zenga.

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Tourist Spending Capacity and Greenhouse Gas Emissions: Evidence from European NUTS2 Regions

Caterina Morelli

Abstract This paper examines the relationship between tourism and regional greenhouse gas (GHG) emissions in 238 EU NUTS2 regions over 2014–2023, accounting for spatial dependence and tourism heterogeneity. Using two-way fixed effects and spatial panel models, we analyse emissions as a function of economic scale, sectoral structure, productivity and tourism intensity, distinguishing higher- and lower-spending segments proxied by hotel and non-hotel accommodation nights.

Key words: Greenhouse gas emissions, panel fixed effect model, regional spillovers, spatial panel models, tourism expenditure

1 Introduction

Tourism has grown rapidly, often outpacing global GDP, while also contributing substantially to greenhouse gas (GHG) emissions, placing the sector at the centre of climate policy debates. A broad macroeconomic literature links emissions to income, structural change, energy use and trade openness [2], while recent spatial econometric studies highlight the importance of regional interdependence and spillovers in emission dynamics [5]. Within this framework, most empirical work on tourism and emissions relies on country-level indicators, implicitly treating tourism as a homogeneous activity. Fewer studies adopt a regional perspective, showing that environmental impacts depend on local transport, accommodation and energy mixes, with particularly strong pressures in coastal and urban areas. However, existing research rarely distinguishes between tourism segments with different spending patterns and largely overlooks the spatial dimension of regional data, leaving open

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how different types of tourism contribute to emissions and how these effects propagate across neighbouring regions.

This paper addresses these gaps by analysing the relationship between tourism and regional GHG emissions in European Union (EU) at the NUTS2 level, thereby exploiting within-country heterogeneity in economic structure, tourism intensity and environmental performance. Moreover, we distinguish tourism by spending capacity [4]. Our research question is not only whether tourism expansion increases emissions, but whether a compositional shift towards higher-spending tourists amplifies or mitigates the environmental footprint of destinations. To account for the spatial correlation of emissions across regions [1], we incorporate spatial dependence in panel models, allowing us to identify local spillovers and obtain unbiased estimates with direct relevance for climate and tourism policy design.

2 Data and Methodoloy

The empirical analysis uses a panel of 238 EU NUTS2 regions over 2014–2023. Core variables are drawn from ARDECO, which provides harmonised regional accounts, productivity indicators and GHG emissions, and are complemented with regional tourism statistics from Eurostat. The dependent variable is the logarithm of total regional GHG emissions from human activities, measured in thousand tonnes of CO2 equivalent and denoted by $\ln Eit$ for region i in year t. Control variables follow standard spatial emission models [5, 2]. Economic scale is captured by real GDP per region and its square (in logs), while economic structure is measured by value added per capita in agriculture (NACE A) and in industry and energy (NACE B–E). Labour productivity is proxied by real GDP per hour worked. Tourism intensity is measured by annual tourist nights, disaggregated by accommodation type. We distinguish hotel nights (NACE I551) from other short-stay accommodation such as B&Bs, campsites and hostels (NACE I552–I553). In logarithms, these variables, denoted T_{it}^{H} and T_{it}^{O}, proxy higher- and lower-budget tourism segments, respectively. This interpretation is supported by evidence that tourists staying in hotels tend to exhibit higher travel expenditures than those choosing alternative accommodation types [4].

The benchmark analysis is M1, a two–way fixed effects panel model of the form

$$\begin{aligned} \ln E_{it} = \alpha_i + \tau_t + \beta_1 \log(\mathrm{GDP}_{it}) + \beta_2 \left[\log(\mathrm{GDP}_{it})\right]^2 + \beta_3 \mathrm{GVA}_{it}^{A} \\ + \beta_4 \mathrm{GVA}_{it}^{BE} + \beta_5 \mathrm{Prod}_{it} + \beta_6 T_{it}^{H} + \beta_7 T_{it}^{O} + u_{it}, \end{aligned} \tag{1}$$

where α_i are region fixed effects, τ_t year fixed effects and u_{it} is an idiosyncratic error term. The β_6 and β_7 coefficients on the tourism variables are of primary interest. Eq. (1) is estimated by within (fixed effects) regression using the `plm` R-package with two–way effects.

Spatial dependence is introduced through a row–normalised geographic weights matrix W based on the 20 nearest neighbours for each region. For each region i, the

20 closest neighbours (excluding itself) are assigned a raw weight of 1 and all others 0 [1]. The matrix is then row normalised so that $\sum_j w_{ij} = 1$. This matrix captures spatial proximity and it is used both in spatial error and spatial lag specifications. As a robustness check, the 10 nearest neighbours matrix are used. To allow for spatial autocorrelation in the disturbances, we estimate M2, a spatial error model where the error term follows a spatial autoregressive process:

$$\ln E_{it} = \alpha_i + \tau_t + X_{it}\beta + u_{it}, \;\; u_{it} = \rho \sum_j w_{ij} u_{jt} + \varepsilon_{it} \tag{2}$$

with X_{it} collecting all regressors in Eq. (1). The parameter ρ measures the degree of spatial correlation in the composite errors. As an alternative, we consider M3 a spatial lag specification where the dependent variable enters with a spatial lag:

$$\ln E_{it} = \alpha_i + \tau_t + \lambda \sum_j w_{ij} \ln E_{jt} + X_{it}\beta + \varepsilon_{it}, \tag{3}$$

where λ is the spatial autoregressive coefficient. In this case, emissions in each region depend directly on emissions in neighbouring regions, for example due to shared technologies, policy spillovers or physical diffusion of pollutants. This model is estimated with `spml` [3]

3 Empirical findings and Conclusion

M1 in Table 1 confirms the role of key economic drivers. Income is strongly and non-linearly related to emissions: GDP enters positively while its square is negative, indicating rising emissions at a decreasing rate. Sectoral composition also matters, with agricultural value added associated with lower emissions and industry–energy value added showing a positive but only marginally significant effect. Labour productivity has a negative and significant coefficient, consistent with higher efficiency or cleaner technologies. Tourism effects are small but informative. The coefficient on hotel nights is negative and significant in the fixed effects and spatial lag models, and close to the 10% level in the spatial error model. By contrast, nights in other, typically lower-cost, accommodation have a positive but insignificant coefficient. Conditional on controls and fixed effects, regions with relatively more high-cost hotel tourism tend to exhibit slightly lower emissions, while low-cost tourism shows no clear association. M2 and M3 confirm spatial dependence, with positive and highly significant spatial error and lag coefficients, indicating correlated shocks and spillovers across neighbouring regions; results are robust to a 10-nearest-neighbours matrix. The pattern is consistent with high-spending tourists having a relatively smaller environmental impact, but the evidence is not strong enough to support a yet definitive conclusion.

The results point to future research needs, including disentangling the specific emission channels affected by tourism, improving the measurement of tourist spend-

Table 1 Determinants of regional GHG emissions, all models include region and year fixed effects, standard errors in parentheses. $^{\dagger}p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	M1 (Panel Model)	M2 (Spatial Error)	M3 (Spatial lag)
log(GDP)	2.346 (0.241)***	2.231 (0.232)***	2.205 (0.227)***
$[\log(\text{GDP})]^2$	-0.092 (0.012)***	-0.086 (0.011)***	-0.087 (0.011)***
GVA_A per capita	-2.369 (0.365)***	-2.463 (0.357)***	-2.271 (0.344)***
GVA_{BE} per capita	0.177 (0.114)	0.223 (0.112)*	0.275 (0.108)*
Labour productivity	-0.003 (0.001)**	-0.004 (0.001)***	-0.003 (0.001)**
log(hotel nights)	-0.028 (0.013)*	-0.023 (0.013)†	-0.027 (0.012)*
log(other nights)	0.008 (0.006)	0.010 (0.006)†	0.009 (0.006)
Spatial error ρ	–	0.240 (0.041)***	–
Spatial lag λ	–	–	0.215 (0.039)***
Region and Year FE	Yes	Yes	Yes
Observations	2380	2380	2380

ing beyond accommodation type, and analysing heterogeneous effects across regions and energy-policy contexts to better assess the compatibility of high-spending tourism with climate goals.

Acknowledgements Funded by the European Union – NextGenerationEU, Mission 4 Component 1.5 – ECS00000036 – CUP B63B22000010001 and by the project "SMARTDECO - Energia e Turismo in Aree Montane Fragili: Strategie e metodologie per il Decoupling", CUP B59J25000540007.

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Tourists' Perception of Destination Congestion: Evidence from Southern Italy

Furio Urso, Martina Aronica, Davide Piacentino and Maria Francesca Cracolici

Abstract This paper investigates perceived destination congestion from the tourists' perspective in Southern Italy using data from a survey of 5,000 domestic and foreign visitors. We adopt a two-step selection approach: the first step models the likelihood of perceiving congestion based on socio-demographic characteristics and travel style; the second step assesses the intensity of perceived congestion using experiential indicators of crowding, infrastructure strain, and authenticity loss. The results suggest that destination congestion is not only a matter of visitor volume, but of how tourists interact with destinations, offering insights for more targeted and experience-oriented management strategies.

Key words: Destination congestion, Two-step selection model, Travel pattern

1 Introduction

Overtourism has become a key issue in destinations management, as the rapid growth and spatial concentration of visitor flows increasingly generate pressure

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on destinations (UNWTO, 2018). When tourism demand exceeds local capacities, negative effects may arise not only for residents and local systems but also for tourists themselves, through congestion, reduced service quality, and a deterioration of the overall travel experience (WTTC, 2017). Despite its relevance, congestion remains a challenging phenomenon to measure, particularly due to its subjective and perception-based nature. The existing literature has mainly approached congestion from the residents' perspective, focusing on social carrying capacity and local attitudes toward tourism development (Namberger et al., 2019; Gonzalez et al., 2018). While this perspective is essential, it provides only a partial view of the phenomenon. Tourists are typically treated as drivers of congestion rather than as stakeholders who directly experience its negative consequences. As a result, empirical evidence on destination congestion from the demand side remains limited, despite the potential relevance of tourists' perceptions for destination management and policy design (Krajickova et al., 2022, Joo et al., 2019).

This paper contributes to the literature by proposing a tourist-based measure of destination congestion that explicitly distinguishes between the perception of crowding and its perceived intensity. Using data from a survey conducted on a sample of 5,000 Italian and foreign tourists on vacation, the analysis focuses on the provinces of Southern Italy, an area characterised by growing tourism demand and heterogeneous destination profiles. The study adopts a two-step selection framework to account for the non-random nature of perceived destination congestion. In the first step, the probability that a tourist perceives the destination as crowded is modelled as a function of socio-demographic individual characteristics (Szromek et al., 2019). In the second step, conditional on having perceived crowding, an ordered response model is employed to assess the role of experiential factors in explaining the intensity of congestion perception. By separating the determinants of perception from those influencing its intensity, the paper provides a concise and behaviourally grounded contribution to the measurement of perceived destination congestion from the tourist perspective.

The remainder of the paper is organised as follows. Section 2 describes the primary data and presents the two-step modelling framework. The final section presents results and concluding remarks.

2 Data and Model

To investigate tourists' perceptions of destination congestion, we rely on survey data collected from domestic and inbound tourists staying for at least six consecutive days at destinations located in Southern Italy. The survey was conducted on-site during tourists' stays as part of the GRINS (Growing Resilient, INclusive and Sustainable) project funded by the European Union. Using a Computer-Assisted Personal Interviewing (CAPI) methodology, the survey gathered detailed information on tourists' spatial behaviour, mobility patterns, and perceived crowding at the des-

tination. The final random sample consists of 5,000 complete interviews, stratified by key socio-demographic characteristics and collected in August 2025.

We perform a two-step selection approach, where the first step, using a probit specification, models the probability that a respondent perceives congestion during their stay. Let S_i^* denote the latent propensity to perceive congestion:

$$S_i^* = \mathbf{Z}_i'\gamma + u_i, \tag{1}$$

where $\mathbf{Z}_i$ includes socio-demographic characteristics (age and household typology) and self-reported travel style (i.e. stationary, semi-itinerant, or itinerant), and u_i is a standard normal error term. The observed outcome is:

$$S_i = \begin{cases} 1 & \text{if } S_i^* > 0, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

The second step examines the intensity of perceived destination congestion, measured as an ordered variable having three levels: *Low*, *Medium*, and *High*.

To account for selection bias, we include the Inverse Mills Ratio (IMR), λ_i, derived from the first-stage probit. The IMR represents the expected value of the first-step error conditional on selection, capturing the correlation between unobserved factors affecting both the likelihood to perceive congestion and its intensity. Including λ_i corrects for sample selection bias and ensures consistent estimates of the effects of interest. The latent perception of destination congestion intensity Y_i^* is modelled as:

$$Y_i^* = \mathbf{X}_i'\beta + \delta\lambda_i + \varepsilon_i, \tag{3}$$

where $\mathbf{X}_i$ includes a binary indicator capturing the travel pattern (single-destination versus multi-destination trips), together with a set of experiential congestion indicators reflecting tourists' perceived pressure at the destination. These indicators capture key dimensions of destination congestion, namely perceived crowding, saturation of tourism-related infrastructure and services, and perceived loss of destination authenticity.

3 Results and Concluding Remarks

The analysis indicates that socio-demographic characteristics, household composition, and travel style play a relevant role in shaping the likelihood of perceiving destination congestion. Older tourists tend to be less likely to report congestion compared to younger visitors, suggesting differences in sensitivity or expectations toward congestion-related phenomena. Household structure also matters, as individuals travelling in couples, with or without children, are more prone to perceive congestion than those travelling alone. Moreover, mobility style, captured through self-reported responses, significantly affects congestion perception. Itin-

erant tourists perceive higher crowding than stationary ones, which may reflect a broader experiential background accumulated through habitual multi-destination travel. The intensity of perceived destination congestion is mainly influenced by experiential indicators—such as crowding, infrastructure strain, and loss of authenticity—and by travel patterns, even if its effect is only significant for shifts from *Low* to *Medium* levels of perceived congestion, suggesting that extreme perceptions (*High*) are relatively uncommon and likely driven by threshold effects or unobserved individual characteristics. Additionally, tourists interviewed at the destination who report that their current holiday includes overnight stays in multiple destinations exhibit a higher intensity of perceived destination congestion compared to single-destination tourists. In sum, the findings indicate that, in the southern regions of Italy, the likelihood of perceiving overtourism from the tourists' point of view is primarily associated with individual characteristics and travel behaviour, while the perceived intensity is shaped by experiential dimensions of tourism pressure. From a policymaker perspective, addressing experiential factors that increase the intensity of perceived crowding could help preserve tourist satisfaction and, in turn, support the long-term competitiveness of Southern Italian destinations.

Acknowledgements This work was carried out within the two projects: GRINS (Growing Resilient, INclusive and Sustainable) funded by the European Union Next-GenerationEU (National Recovery and Resilience Plan, NRRP, Mission 4, Component 2, Investment 1.3 – D.D. 1558 11/10/2022, PE00000018, Spoke 7 Territorial Sustainability); and GREENGO (Competitiveness for a stronger and more sustainable Italian economy) funded by the Ministry of University and Research, PRIN 2022 – D.D. 104, 02/02/2022. This manuscript reflects only the authors'views and opinions, neither the European Union, the European Commission nor the Ministry of University and Research can be considered responsible for them.

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Towards spatially aware BoD indicators: a proposal for integrating Benefit-of-the-Doubt and ESDA for the construction of regional synthetic indices

Giuseppe Notarstefano and Giuseppe Terzo

Abstract This paper aims to leverage spatial information in the construction of a composite indicator. Starting from a well-known method (the Benefit-of-the-Doubt method), some applications are proposed within the SDG indicators of the 2030 Agenda.

Key words: Benefit-of-the-Doubt (BoD) method, Composite Indicator, Exploratory Spatial Data Analysis (ESDA)

1 Introduction

The Benefit-of-the-Doubt (BoD) method has become established as one of the most flexible approaches to constructing composite indicators grounded in DEA-type techniques, thanks to its ability to determine the weights of the underlying indicators endogenously and thereby reduce arbitrariness in their selection [3]. In recent years, BoD has been widely applied in socio-economic and health settings to support comparative assessments of performance and well-being, including in institutional and policy contexts [4]. In parallel, advances in Exploratory Spatial Data Analysis (ESDA) and spatial econometrics have shown that spatial dependence and spatial heterogeneity are essential features in the analysis of territorial disparities. Tools

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such as Global Moran's I, Local Indicators of Spatial Association (LISA), and the Moran scatterplot are now well established within regional science [1], [2].

More recently, spatial thinking has also informed the construction of composite indicators of regional well-being, notably through hierarchical frameworks and spatial factor models [5] . Yet BoD-based indicators are still most often built under an implicit assumption of independence across units. This can be limiting in practice, because scores may reflect not only 'how well a place performs' but also the advantages, constraints, and spillovers associated with its territorial context.

2 Research aim

Against this backdrop, the literature still offers relatively few contributions that explicitly combine BoD with the spatial dimension, both at the stage of indicator construction and in the subsequent analysis of the territorial distribution of scores. This study, therefore, sets out a research agenda to bridge BoD and ESDA by introducing a spatially aware BoD framework for assessing regional performance, with a particular focus on a potential application to SDGs 3 (Good Health and Well-being), 7 (Affordable and Clean Energy), 13 (Climate Action), and 16 (Peace, Justice and Strong Institutions). Considering these goals together allows us to explore the interconnections between environmental health, energy sustainability, climate resilience, and institutional quality, and to make the systemic link between peace and the environment more visible from a territorial perspective.

This research aims to develop a spatial extension of the BoD method that directly incorporates information on the spatial neighbourhood of statistical units (e.g. regions, provinces, or municipalities) into the construction of the composite indicator. The extension benchmarks each unit against its surrounding context, rewarding those that perform better than nearby areas and penalising those that underperform relative to their neighbourhood, while remaining faithful to DEA/BoD logic. The resulting composite indicator is intended to be interpreted both as a measure of individual performance and as an index of relative positioning within the territorial context.

The approach is designed to be applicable across a range of thematic domains (socio-economic well-being, the quality of public services, sustainability, health-system performance, and so forth), with particular attention to settings characterised by strong territorial interdependencies, spatial clustering, and potential spillover effects. In this sense, the framework is intended to complement, rather than replace, standard BoD scores by providing an explicitly context-aware perspective that can be subjected to robustness checks under alternative neighbourhood definitions and modelling choices.

3 Proposed framework

In practical terms, the proposed framework defines a spatially aware Benefit-of-the-Doubt composite indicator that incorporates the spatial proximity structure of statistical units (regions, provinces, municipalities), for instance, through a spatial weights matrix based on contiguity or distance.

It enables locally grounded benchmarking by identifying units that over-perform relative to comparable neighbouring areas. It also highlights units that appear to lag behind their local context, helping to distinguish absolute underperformance from disadvantageous territorial conditions. Finally, it supports ESDA-informed interpretation of results - for instance, through Moran's I, LISA, and Moran scatterplots of the composite scores - alongside sensitivity analyses to alternative specifications.

The approach is intended to be particularly useful for the territorial monitoring of the Sustainable Development Goals (SDGs), where the spatial dimension is central to understanding inequalities and to designing and evaluating place-based policies. By combining efficiency-oriented benchmarking with spatial diagnostics, the proposed indicator can help policymakers identify clusters of vulnerability and pockets of resilience and better target interventions across territories.

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Underreporting and the measurement of inequality: a joint income-selection model for Italian households

Maria Felice Arezzo, Giuseppina Guagnano, Alberto Arcagni, Domenico Vitale and Riccardo Di Stefano

Abstract Measuring economic inequality is frequently compromised by informational biases in survey data. This paper addresses income underreporting by implementing a joint income-selection model that explicitly accounts for the misclassification of reporting units. Our results reveal significant distributional compression: the Gini index decreases by 10.91%, falling from an observed 0.3051 to a corrected 0.2718. This shift is primarily driven by the correction of "spurious dispersion" at the lower end of the distribution, where underreporting artificially inflates perceived poverty. These findings suggest that raw survey data overestimate intra-sample inequality, necessitating adjustments for reliable policy evaluation.

Key words: Gini index, Undereporting, Miscassification.

1 Introduction

The core objective of this paper is to produce a refined estimate of economic inequality by "cleaning" the reported data from informational biases. To achieve this, we leverage household consumption as a latent signal of the true standard of living. By modeling the difference between expenditure and income, we reconstruct a distribution that is internally consistent and resilient to the noise inherent in self-reported figures.

As the SHIW inherently lacks representation of the wealthiest 1% of the population, our analysis does not attempt to provide an exhaustive national inequality figure. Instead, our contribution establishes a more robust calculation of the Gini index within the observable range of the sample.

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2 The model

The traditional approach to analyzing the determinants of income is based on the Mincerian equation [2]. In this setup, the logarithm of household income Y_i is modeled as a linear function of observable characteristics:

$$\ln(Y_i) = X_i\beta + \varepsilon_i \tag{1}$$

where X_i represents a vector of socio-economic variables (such as education, age, and geographical location) and $\varepsilon_i \sim N(0, \sigma^2)$ is the stochastic error term. However, this specification assumes that the reported income Y_i^{obs} is an accurate reflection of the true latent income Y_i^{true}. In the presence of systematic underreporting, this assumption is violated, leading to biased estimates of the coefficients β and, consequently a distorted calculation of the Gini index.

To address this bias, we introduce a latent binary variable E_i^*, which serves as an indicator for the true reporting behavior of the household:

$$E_i^* = \begin{cases} 1 & \text{if the household underreports its income} \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

In existing literature [3], E_i^* is often identified through the "income-consumption gap." Following the permanent income hypothesis, if observed consumption C_i significantly exceeds observed income Y_i^{obs}, the household is typically flagged as an underreporter. However, we argue that this deterministic approach is limited: both income and consumption are measured with error, and we cannot observe the net result of these errors. A simple gap might reflect dissaving, gifts, or measurement noise rather than intentional underreporting. To relax the deterministic assumption, we introduce two misclassification parameters as in [1], α_0 and α_1, which represent the probability of incorrectly observing the latent reporting status:

- $\alpha_0 = P(E_i = 1|E_i^* = 0)$: The probability of a "False Positive" (identifying a truthful household as an underreporter).
- $\alpha_1 = P(E_i = 0|E_i^* = 1)$: The probability of a "False Negative" (identifying an underreporting household as truthful).

By incorporating these parameters, the observed indicator E_i becomes a noisy signal of the latent status E_i^*, allowing the model to distinguish between systematic underreporting and random measurement error.

We assume that the underlying latent propensity to underreport can be modeled in a regression framework, hence:

$$E_i^* = \mathbb{I}(Z_i\gamma + u_i > 0) \tag{3}$$

where Z_i is a vector of predictors for the reporting behavior. To account for unobserved factors that could affect income and the decision to underreport — we assume that the error terms (ε_i, u_i) follow a bivariate normal distribution:

$$\begin{pmatrix} \varepsilon_i \\ u_i \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & 1 \end{pmatrix} \right) \tag{4}$$

The joint density of the observables $(\ln Y_i, E_i)$ leads to the following log-likelihood function for the sample:

$$\ln \mathscr{L} = \sum_{i=1}^{n} \ln \left[\frac{1}{\sigma} \phi \left(\frac{\ln Y_i - X_i\beta}{\sigma} \right) \cdot P(E_i | \ln Y_i) \right] \tag{5}$$

By expressing $P(E_i|\ln Y_i)$ as a function of $P(E_i^*|\ln Y_i)$ and the misclassification probabilities α_0 and α_1, and using the properties of the bivariate normal distribution, the individual likelihood contribution for household i becomes:

$$\mathscr{L}_i = \frac{1}{\sigma} \phi \left(\frac{\ln Y_i - X_i\beta}{\sigma} \right) [\Psi_i(1-\alpha_1) + (1-\Psi_i)\alpha_0]^{E_i} [\Psi_i\alpha_1 + (1-\Psi_i)(1-\alpha_0)]^{1-E_i} \tag{6}$$

$$\Psi_i = \Phi \left(\frac{Z_i\gamma + \frac{\rho}{\sigma}(\ln Y_i - X_i\beta)}{\sqrt{1-\rho^2}} \right), \tag{7}$$

and ϕ and Φ denote the standard normal density and cumulative distribution functions, respectively. Maximizing this function allows us to retrieve consistent estimates of β, σ, and ρ, which are subsequently used to simulate the "clean" income distribution and calculate the corrected Gini index.

A well-known challenge in discrete choice models with misclassification is the simultaneous identification of the misclassification probabilities, α_0 and α_1.

To ensure model stability and a parsimonious specification, we impose the constraint $\alpha_0 = \alpha_1 = \alpha$, which implies a symmetric error probability in the reporting indicator[1]. Furthermore, rather than attempting to estimate α as a free parameter, we adopt a *grid search* approach. We calibrate the model across a range of plausible values, $\alpha \in \{0.02, 0.05, 0.10, 0.15\}$, representing different degrees of informational noise within the SHIW dataset.

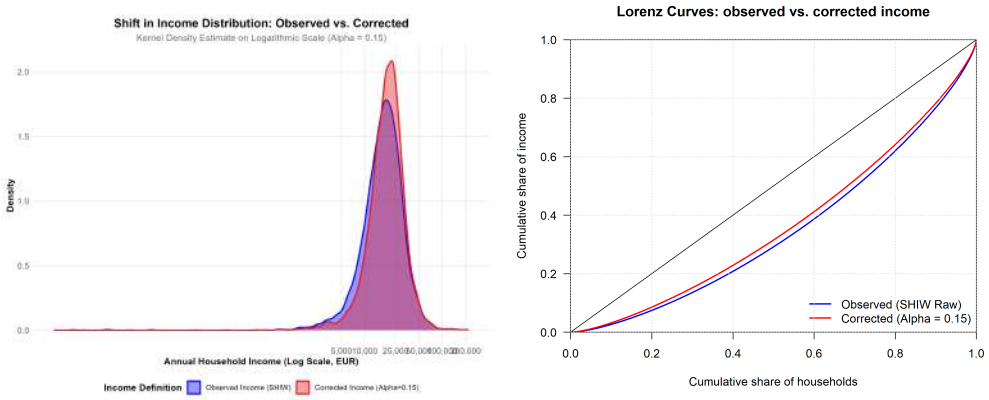
This strategy allows us to treat α as a tuning parameter, providing a data-driven selection based on the model's goodness-of-fit. Specifically, the optimal value is selected by maximizing the log-likelihood function:

$$\alpha^* = \arg\max_{\alpha} \ln \mathscr{L}(\alpha; \hat{\beta}, \hat{\gamma}, \hat{\sigma}, \hat{\rho}) \tag{8}$$

By performing this grid search, we provide a "stress test" for our results, ensuring that the estimated Gini index is robust to different assumptions regarding the quality of the survey's reporting. The model with $\alpha = 0.15$ yielded the highest log-likelihood, suggesting that this specific level of baseline noise best captures the underlying informational structure of the Italian sample.

[1] This assumption seems quite plausible, given how E_i has been defined.

3 Results



(a) Kernel Density Estimate (b) Lorenz Curves

Fig. 1: Comparison btw observed and corrected income distributions ($\alpha = 0.15$).

The empirical impact of the correction model is summarized in Figure 1, which highlights how accounting for informational noise fundamentally reshapes the perceived income distribution of the SHIW sample.

The interpretation of this result is twofold. First, these results demonstrate that informational bias is non-randomly distributed, primarily affecting the lower deciles of the observed income scale, despite the assumption of symmetric misclassification errors. Second, once the noise is filtered through the consumption-proxy model, the intra-sample inequality appears significantly lower. This suggests that the SHIW data, when uncorrected, may provide an overestimation of economic disparity due to the inconsistent reporting of resources across the socio-economic spectrum.

By addressing structural estimation biases, our approach prevents the erosion of statistical accuracy, thereby ensuring that social protection and redistributive measures are grounded in an empirically sound assessment of economic disparities.

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Urban Heat Islands as Economic Externalities: Evidence from Bari

Valeria Marzocca

Abstract Urban economic transition generates environmental externalities that are unevenly distributed across space, among which urban heat islands (UHI) have significant impacts on public health, energy consumption, and social well-being. This study examines UHI as an externality of economic transition in the city of Bari, adopting a neighborhood-scale statistical approach. By integrating satellite-derived surface temperature data with socioeconomic indicators, a multivariate regression model is estimated to explain intra-urban thermal differences. The results reveal a negative and significant relationship between average income and urban heat island intensity, highlighting the distributive dimension of the phenomenon and providing useful insights for urban climate adaptation policies.

Key words: urban heat islands; economic transition; multivariate regression; urban inequalities; Bari

1 Introduction

Economic transition is one of the main processes transforming contemporary urban economies and, alongside the benefits in terms of growth and competitiveness, generates significant environmental externalities. Among these, urban heat islands (UHI) represent a systematic increase in temperatures in urbanized areas compared to surrounding rural areas, due to the concentration of impervious surfaces, the reduction of vegetation cover, and the intensity of human activities [1,5].

The literature highlights that UHIs are not only a climatic phenomenon but also an economic and social issue, associated with higher health costs, reduced labor productivity, and increased energy demand, with effects unevenly distributed across urban space [2,8,9]. Despite growing interest, neighborhood-scale analyses in medium-sized cities remain limited [10].

This study examines UHIs as an externality of economic transition in the city of Bari, adopting a neighborhood-scale statistical approach to evaluate the role of

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socioeconomic and settlement characteristics in the spatial distribution of urban heat island intensity, with particular attention to policy implications.

2 Methodology

The analysis is conducted at the neighborhood scale, considering the 17 neighborhoods of the Municipality of Bari as the units of observation. This scale allows capturing intra-urban differences in urban heat island intensity and linking them to local socioeconomic characteristics [6].

2.1 Units of Analysis and Data

The dependent variable is surface urban heat island intensity (SUHII), defined as the relative warmth of a pixel compared to the temperature range of its altitudinal belt, thereby highlighting local thermal anomalies rather than absolute temperatures. The indicator is derived from Landsat 8 and 9 satellite data (USGS) for the summer of 2025 [7], with a native spatial resolution of 100 m, resampled to 30 m, and subsequently aggregated at the neighborhood level. Higher SUHII values indicate less favourable microclimatic conditions (Figure 1) [3,4].

The explanatory variables include socioeconomic and demographic indicators: average taxable income, percentage of the population over 74 years old, percentage of children under 5 years old, population density, and employment rate.

These variables represent the main channels through which urban economic transition can translate into environmental inequalities and exposure to heat stress. Socioeconomic data come from official sources (2022 Population Census and the Italian Revenue Agency) and were harmonized in a GIS environment to ensure spatial compatibility.

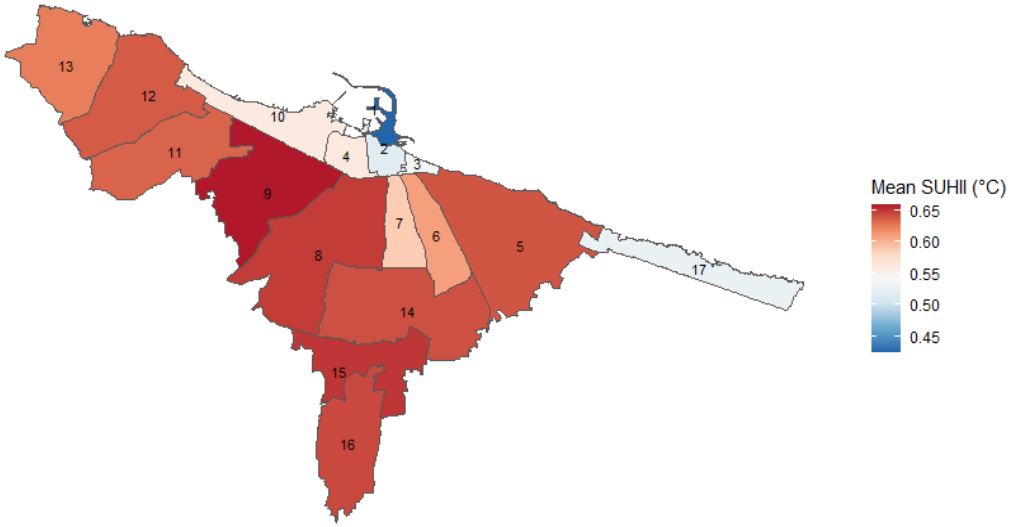
2.2 Model Specification

To assess the association between socioeconomic characteristics and SUHII, a multivariate linear regression model of the following form is estimated using the ordinary least squares method. Given the small sample size, the analysis is exploratory and aimed at identifying (net) statistical associations rather than causal relationships.

Multicollinearity diagnostics are conducted using the Variance Inflation Factor (VIF), which quantifies the inflation of individual coefficient variances due to correlations among regressors, and the multicollinearity condition number, which provides a global measure of linear dependence in the design matrix. Low values of

both measures indicate the absence of multicollinearity concerns, confirming the stability of the estimates.

Figure 1: Mean SUHII of the City of Bari, by Neighborhood



Note: Neighborhood codes: 1 – San Nicola, 2 – Murat, 3 – Madonnella, 4 – Libertà, 5 – Japigia, 6 – San Pasquale, 7 – Carrassi, 8 – Picone, 9 – Stanic, 10 – Marconi San Girolamo Fesca, 11 – San Paolo, 12 – Palese - Macchie, 13 – Santo Spirito, 14 – Carbonara di Bari, 15 – Ceglie del Campo, 16 – Loseto, 17 – Torre a Mare.

3 Results

The model shows good explanatory power (adjusted $R^2 = 0.590$) and is globally significant ($p = 0.008$). Average taxable income is negatively and significantly associated with SUHII, indicating lower heat island intensity in more socioeconomically advantaged neighborhoods. The proportion of the elderly population and population density exhibit marginally significant effects, positive and negative respectively. Contrary to initial expectations, population density does not display a positive association with SUHII, suggesting that urban heat exposure in Bari is driven less by demographic concentration per se than by socioeconomic conditions and urban form. In this respect, dense central neighborhoods may benefit from compact morphology and shading effects, whereas less dense peripheral areas are characterized by extensive impervious surfaces, leading to higher surface temperatures. By contrast, the percentage of children and the employment rate do not show statistically significant associations.

4 Discussion and Conclusions

The results show that socioeconomic inequalities are reflected in microclimatic differences across neighborhoods [2], with lower urban heat island intensity in wealthier areas and higher vulnerability associated with an ageing population. The absence of a positive relationship between population density and SUHII suggests that, in Bari, urban heat exposure is influenced more by urban form and socioeconomic conditions than by demographic concentration, with compact central areas benefiting from shading effects and peripheral neighborhoods showing higher surface temperatures. Some limitations related to the scale of analysis should be acknowledged. The neighborhood-level approach, based on a limited number of spatial units, implies an exploratory interpretation of the results rather than causal inference. Moreover, spatial aggregation may mask intra-neighborhood heterogeneity, and surface temperature represents a proxy rather than a direct measure of individual heat exposure. Despite these constraints, the chosen scale is appropriate for highlighting distributive patterns of urban heat and for informing neighborhood-level climate adaptation policies aimed at reducing heat-related inequalities.

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What it takes to be circular: A boosted trees analysis of Italian firms

Fabio Demaria, Cecilia Correggi, Sara Giovanna Mauro and Paolo Di Toma

Abstract Micro and small enterprises (MSEs) are crucial to the transition toward circular business models, yet empirical evidence explaining why some adopt circular practices while others do not remains limited. Using survey data from 816 Italian firms, this study applies a data-driven statistical learning approach to investigate circular economy (CE) adoption. An XGBoost classification model with imbalance adjustment is used to identify key predictors, while nonlinear interactions between variables are examined through Friedman's H-statistic. The results show that CE adoption is not driven by individual factors, but emerges when forward-looking strategic orientation aligns with internal financial resources and structured knowledge, jointly reducing perceived implementation complexity and clarifying the role of incentives. Methodologically, the study shows how modern statistical learning techniques enable fine-grained empirical investigations of strategic change processes toward sustainability.

Key words: Circular Economy; Micro and small enterprises; XGBoost; Feature importance; Interaction effects.

1 Introduction

The transition from linear to circular economy (CE) models has become a strategic priority for advancing sustainable development and resource efficiency. Micro and small enterprises (MSEs) represent more than 95% of European firms and are central to this transition due to their widespread presence in supply chains and regional production systems. However, limited resources, short-term strategic horizons, and lack of knowledge hinder CE adoption [1]. Prior studies typically list enablers and barri-

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ers but overlook how such factors interact statistically to shape adoption outcomes [2]. To address this gap, we develop the following research question:

> *Which factors best predict CE adoption in MSEs, and how do they interact?*

Our contribution lies in applying statistical learning tools to investigate variable importance and interaction effects between variables, providing a methodological blueprint for sustainability studies where theoretical priors are incomplete and interaction effects are expected to be substantial.

2 Data and methods

Sample Description. Data were collected through a primary survey conducted between December 2023 and January 2024 in collaboration with the National Confederation of Crafts and Small and Medium Enterprises (CNA). The final sample ($n = 816$) reflects the structural composition of the Italian productive economy: 80.4% micro-enterprises (<10 employees) and 19.6% small enterprises. Sectoral distribution is diverse: Services (48.7%), Manufacturing (35.5%), and Construction (14.1%). The dependent variable is a binary indicator of CE adoption, where 32.7% of firms reported implementing at least one CE-related practice. Explanatory variables include binary indicators capturing strategic orientation, resource availability, knowledge channels, perceived barriers, and enabling conditions.

2.1 Statistical methods

To model a binary indicator of CE adoption, we employ eXtreme Gradient Boosting (XGBoost), a scalable implementation of gradient boosted decision trees [3]. Let $(\mathbf{x}_i, y_i)$, for $i = 1, \ldots, n$, denote the dataset with predictors $\mathbf{x}_i \in \mathbb{R}^p$ and binary outcomes $y_i \in \{0, 1\}$. The model approximates the latent function $f(\mathbf{x})$ as an additive ensemble of K regression trees:

$$f(\mathbf{x}) = \sum_{k=1}^{K} f_k(\mathbf{x}), \quad f_k \in \mathcal{F}, \tag{1}$$

where each f_k partitions the feature space and assigns learned weights to terminal nodes. Predicted probabilities are computed using the logistic link. Training minimizes a regularized objective balancing predictive loss and model complexity:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l(y_i, \hat{y}_i^{(t-1)} + f_t(\mathbf{x}_i)) + \Omega(f_t), \tag{2}$$

where $l(\cdot)$ denotes logistic loss and $\Omega(f_t)$ penalizes tree size and weight magnitudes. To prevent the majority class from dominating the learning process, the algorithm adjusts instance weights as:

$$w_i = \begin{cases} \frac{C_1}{C_0}, & \text{if } y_i = 1, \\ 1, & \text{otherwise,} \end{cases} \tag{3}$$

with C_1 and C_0 representing class counts. This increases the penalization of misclassified minority cases, mitigating bias.

Feature importance. Feature relevance is quantified using gain, which measures the reduction in regularized loss obtained by splitting on a given feature:

$$\text{Gain} = \frac{1}{2}\left[\frac{G_L^2}{H_L+\lambda} + \frac{G_R^2}{H_R+\lambda} - \frac{(G_L+G_R)^2}{H_L+H_R+\lambda}\right] - \gamma, \tag{4}$$

where G_L and H_L (and G_R, H_R) denote aggregated gradients and Hessians. Summing gain across all splits and boosting rounds yields a cumulative relevance measure:

$$\text{Total Gain}_F = \sum_{t,n} \text{Gain}_{n,t}. \tag{5}$$

This approach identifies predictors that most improve predictive accuracy.

Feature interaction. To quantify non-additive effects among predictors, we apply Friedman's H-statistic. Let $f_j(x_j)$ denote the partial dependence of feature x_j and $f_{jk}(x_j, x_k)$ their joint dependence. Interaction strength is defined as:

$$H_j^2 = \frac{\mathbb{E}[(f(\mathbf{x}) - f_j(x_j) - \sum_{k\neq j} f_k(x_k))^2]}{\mathbb{E}[f(\mathbf{x})^2]}, \tag{6}$$

representing the proportion of explained variance attributable to feature interactions.

Interaction visualization. Interaction structure is represented through a symmetric matrix $\mathbf{M}$:

$$M_{jk} = \begin{cases} H_{jk}, & j \neq k, \\ \text{Gain}(x_j), & j = k, \end{cases} \tag{7}$$

where diagonal entries encode importance and off-diagonal entries encode interaction magnitudes. Seriation-based reordering and heatmap visualization facilitate interpretation [5].

3 Empirical results

The XGBoost model (AUC = 0.91; precision = 0.794) identifies a small subset of relevant predictors, including internal financial resources (own funds), perceived future strategic relevance of CE, structured knowledge sources (training, associations), and perceived implementation complexity. Figure 1 visualizes the interaction matrix derived from Friedman's H-statistic.

Strong interaction patterns emerge between strategic orientation and internal financial resources, between informal knowledge and perceived implementation complexity, and between informal knowledge and perceived lack of incentives. These interactions suggest that CE adoption in MSEs is most likely when forward-looking strategic intent aligns with resource readiness and structured knowledge, reducing perceived complexity.

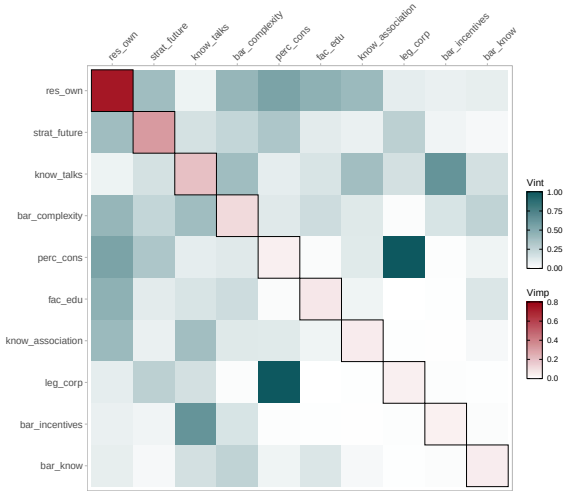

Fig. 1: Heatmap of variable interactions.

Note(s): Red intensity denotes variable importance; green intensity denotes interaction strength.

4 Discussion and conclusion

Our findings show that CE adoption in micro and small firms is not driven by isolated drivers but by the convergence of strategic intent, internal resources, and knowledge structures. These interaction dynamics align with the Resource-Based View (RBV) [6], which emphasizes that advantages stem from complementary resource configurations rather than single inputs. From a methodological perspective, the proposed approach improves upon traditional linear or additive models by jointly performing data-driven feature selection and uncovering complex, nonlinear interactions among predictors. From a policy perspective, the results suggest that financial incentives alone are insufficient; their effectiveness depends on complementary measures that reduce perceived complexity and strengthen knowledge acquisition.

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When Big Data Improve Nowcasting During Economic Shocks: Evidence from Italian Unemployment

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Abstract. Timely unemployment statistics are essential during economic transitions, yet official labour market data are released with delays. This paper evaluates whether Big Data, specifically Google Trends (GT), provide predictive content for Italian unemployment nowcasting under different volatility regimes. Using multi-window GT stitching, MIDAS aggregation, and ridge regression with expanding-window time-series cross-validation, we document modest average gains in out-of-sample accuracy, with substantial improvements during high-volatility labour market shocks such as the COVID crisis. GT-based indicators show negligible contributions in stable periods, suggesting their usefulness is regime-dependent.

Key words: Big Data, Google Trends, MIDAS, Nowcasting, Regime dependence.

1 Introduction

Timely labour market information is crucial during periods of economic change, but official unemployment statistics are released with delays of up to several weeks, motivating the use of alternative high-frequency data sources. Google Trends (GT) data have been applied to labour market forecasting and nowcasting, with evidence suggesting that their predictive performance depends on the country, the period considered, and the volatility regime. While some studies report significant gains (D'Amuri and Marcucci, 2017), others document mixed, context-dependent results (Fondeur and Karame, 2013; Tuhkuri, 2016); nevertheless, early contributions show

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that internet search behaviour contains timely information on labour market conditions (Askitas and Zimmermann, 2009; McLaren and Shanbhogue, 2011).

This paper investigates whether and when Google Trends improve Italian unemployment nowcasting, focusing on post-pandemic accuracy and regime dependence. We employ a mixed-frequency framework combining MIDAS aggregation and regularised regression, and evaluate forecasts using the Diebold–Mariano (1995) and Clark–West (2007) tests.

2 Data and Methodology

This section describes the data sources and the empirical framework used to evaluate the contribution of Big Data to unemployment nowcasting.

The target variable is the monthly change in the seasonally adjusted Italian unemployment rate Δu_t, sourced from ISTAT (April 2016 – August 2025). Weekly GT indices for keywords related to job search and unemployment ("offerte di lavoro", "disoccupazione") are reconstructed using multi-window stitching.

Weekly Google Trends (GT) series are reconstructed using a multi-window stitching procedure based on five overlapping five-year windows, rescaled through median ratio normalization to ensure temporal consistency. The target variable is the monthly change in the seasonally adjusted unemployment rate, denoted as Δu_t,

Weekly GT indicators are aggregated to the monthly frequency using a recency-weighted MIDAS approach (Ghysels et al., 2004; Foroni and Marcellino, 2014). Specifically, the monthly aggregated indicator $X_t^{(m)}$ is defined as:

$$X_t^{(m)} = \sum_{k=0}^{K} w_k(\lambda) x_{t-k}^{(w)}, \qquad w_k(\lambda) = \frac{\lambda^k}{\sum_{j=0}^{K} \lambda^j}, \qquad \lambda \in (0,1),$$

where $X_{t-k}^{(w)}$ denotes weekly GT observations, k=0 corresponds to the most recent week within the month, K is the maximum lag length, and λ controls the decay rate of the weighting scheme. Lower values of λ place more weight on recent observations.

The aggregated GT indicators, together with lagged values of Δu_t and an optional delta-correction term, are included in a ridge regression framework to address multicollinearity and overfitting. Hyperparameters are selected via expanding-window time-series cross-validation, with a minimum training sample of 36 months. Forecast accuracy is evaluated using RMSE and MAE. Statistical significance is assessed through Diebold–Mariano (1995) and Clark–West (2007).

3 Results

This section summarizes the main out-of-sample nowcasting results and examines the role of volatility in shaping the contribution of Google Trends indicators.

3.1 Main Performance

Inclusion of GT yields modest average gains relative to standard benchmarks. Three benchmark specifications are considered. The **Persistence** model assumes that the monthly change in unemployment follows a random walk. The **Baseline** model augments this benchmark by including lagged values of $\Delta u_t$and standard autoregressive dynamics. The **Full (GT)** model further incorporates the MIDAS-aggregated Google Trends indicators, allowing an assessment of their incremental predictive content relative to conventional time-series benchmarks.

Table 1: Out-of-sample test: Nov 2022-Aug 2025 (34 obs)

Model	RMSE	MAE	Improvement
Persistence	0.520	0.431	--
Baseline	0.494	0.385	+5.0%
Full (GT)	0.487	0.361	+6.4%

Clark–West tests indicate significant incremental content of GT (p=0.011), while Diebold–Mariano tests versus Persistence show weaker overall evidence (p=0.216).

3.2 Regime-Dependent Performance

To assess whether the contribution of Google Trends depends on labour market conditions, test windows are classified according to unemployment volatility, measured as the standard deviation of Δu_twithin each evaluation period. This allows a distinction between stable regimes and high-volatility episodes associated with economic shocks.

To construct Figure 1, we consider multiple fixed-length out-of-sample evaluation windows (each containing 34 monthly observations, matching Table 1) shifted through the sample. For each window, we compute (i) volatility as the standard deviation of Δu_t within the window and (ii) the RMSE improvement of the Full (GT) model over the persistence benchmark.

Figure 1 relates forecast accuracy improvements over the persistence benchmark to the corresponding volatility levels. The results indicate that GT-based models deliver substantial gains during high-volatility periods, most notably during the COVID-19 shock, where RMSE reductions exceed 20 percent and are statistically significant. By contrast, during low-volatility regimes, the inclusion of GT indicators yields negligible or even negative improvements.

This pattern suggests that Google Trends capture rapid, real-time adjustments in job search behaviour during periods of economic stress, while adding limited information under normal labour market conditions. Cross-validation results further indicate that weighting schemes with λ=0.6 and aggregation windows of 4–8 weeks provide the most stable performance across regimes.

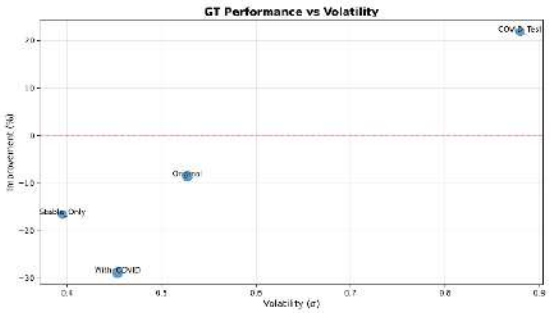

Figure 1: Test-period volatility σ (std of Δu_t within test window) versus RMSE improvement over persistence. Points = test scenarios.

4 Discussion and Conclusions

Our findings confirm the regime-dependent value of Google Trends for unemployment nowcasting. We observe modest average gains, but significant improvements during high-volatility shocks, such as the COVID-19 crisis, where RMSE reductions exceed 20%. Conversely, during stable periods, the inclusion of Google Trends indicators yields negligible or even negative improvements.This evidence aligns with previous research (Choi and Varian, 2012; D'Amuri and Marcucci, 2017; Carriere-Swallow and Labbe, 2013), highlighting that the value of Big Data is contingent rather than structural. Google Trends should therefore be regarded as a complementary, crisis-sensitive data source rather than a routine substitute for official statistics. Future research should focus on developing regime-aware nowcasting frameworks to enhance their conditional predictive power.

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