Determinants of the Ecological Footprint in the EU-27: A Dynamic Factor Model Approach

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Abstract

This paper analyzes the macroeconomic determinants of the Ecological Footprint (EF) per capita in the EU-27 over the period 1970–2019. We propose a Structural Augmented Dynamic Factor Model estimated on a high-dimensional dataset of 104 macroeconomic indicators to capture the latent structure underlying EF dynamics. Common factors are extracted using non-supervised methods (Principal Components) and supervised methods (Partial Least Squares), while observable predictors are selected via a LASSO procedure. The results identify two persistent latent macroeconomic drivers of EF: aggregate economic activity and international trade. The estimated relationships are stable over time and indicate that the association between ecological pressure, business cycle fluctuations, and trade patterns constitutes a structural feature of the European economy. From a policy perspective, the findings imply that effective strategies to reduce ecological pressure require macroeconomic and trade policies capable of weakening the procyclical and trade-related transmission of environmental impacts rather than relying exclusively on efficiency improvements or isolated sectoral measures.

Keywords: Ecological footprint; dynamic factors; economic cycle, international trade, transport

- Funding sources

This research has received support from the Research Group CASSETEM with the financing of the regional government of Aragón (Spain) and from the Spanish Research Agency (project PID2020-114646RB-C44). We are also grateful for the support of the "Fundación Caja Rural de Aragón" Chair.

1. Introduction

Over recent decades, economic growth has substantially improved human welfare, yet this progress has relied on an intensive and often unsustainable use of natural resources, generating persistent ecological pressures at the global scale (Ahmed et al., 2021; Ucan et al., 2024). Conventional environmental indicators, such as greenhouse gas emissions and particularly CO_2, illustrate the magnitude of this challenge. Despite increasing policy commitments, global emissions rose by 1.5 percent between 2021 and 2022, reaching a record level of 36.8 gigatonnes (Guliyev, 2024). However, these indicators capture only part of the environmental burden, as broader dimensions including biodiversity loss, land use change, water stress, and resource depletion remain insufficiently reflected (Yildirim et al., 2024).

To overcome these limitations, the Ecological Footprint[1] has emerged as a comprehensive indicator of environmental pressure. It measures the biologically productive area required to sustain human consumption patterns and absorb associated waste, integrating information on carbon emissions, cropland, grazing land, forest resources, fishing grounds, and built-up land (Wackernagel and Rees, 1998; Ulucak and Lin, 2017; Ansari et al., 2021; Wang et al., 2023). Closely related to this concept is biocapacity[2], which captures the ability of ecosystems to regenerate renewable resources and assimilate waste. Recent evidence points to a persistent and widening imbalance between ecological demand and available biocapacity. In 2022, global Ecological Footprint reached 2.58 global hectares (gha) per capita, while only 1.51 gha per capita were sustainably available. The situation is particularly critical in Europe, where the Ecological Footprint amounted to 4.65 gha per person, and historical assessments indicate that European consumption has exceeded planetary biocapacity for decades, requiring more than three Earths as early as 2019 (Ewing et al., 2010).

[1] According to the Global Footprint Network, the Ecological Footprint is an indicator that measures the impact of a figure (person, community, company, country...) on the environment, based on the amount of natural resources it consumes and the waste it generates. It is expressed in global hectares (gha) and compares this consumption with the planet's capacity to generate these resources and absorb waste.

[2] According to the Global Footprint Network, biocapacity refers to the capacity of ecosystems to regenerate the natural resources that humans consume and to absorb the waste we generate—particularly carbon dioxide (CO_2) emissions—using current technology and management practices, and also it is expressed in gha.

In response to this ecological overshoot, governments and international institutions have promoted ambitious policy frameworks such as the European Green Deal, the European Climate Pact, the Global Pact for the Environment, and the 2030 Agenda for Sustainable Development. These initiatives emphasize decarbonization, circular resource use, and sustainable growth as central policy objectives. Designing effective strategies within this context requires a clear understanding of the macroeconomic forces that drive long-term environmental pressure, particularly in highly integrated and advanced economies such as the European Union.

A growing empirical literature has examined the determinants of the Ecological Footprint, focusing on economic growth, globalization, energy consumption, demographic change, and urbanization. While this literature spans a wide range of regions and country groups, including the EU (Saqib et al., 2023), BRICS (Sun et al., 2023), the G7 and G11 (Ahmad et al., 2021), ASEAN (Ansari, 2022), and Africa (Ehigiamusoe et al., 2022), empirical findings often differ depending on the sample, methodology, and indicators employed. Recent reviews emphasize this heterogeneity and the lack of consensus regarding the relative importance of specific drivers (Quan et al., 2024).

Despite these advances, two limitations remain particularly relevant from a macroeconomic modelling perspective. First, many studies rely on relatively small sets of observable variables, even though environmental pressure arises from the interaction of a large number of highly correlated socioeconomic forces. Second, conventional econometric approaches may fail to capture latent macroeconomic dynamics, such as business cycle fluctuations or structural shifts in international trade, that simultaneously affect environmental outcomes. Recent contributions underline the importance of macroeconomic conditions in shaping environmental pressure measured through Ecological Footprint or CO_2 emissions (Gaies et al., 2022; Kihombo et al., 2021; Wahab et al., 2024). However, only a limited number of studies exploit high-dimensional datasets or factor-based modelling strategies capable of summarizing broad macroeconomic structures.

Addressing these methodological challenges is particularly relevant in the European context, where environmental outcomes are shaped not only by energy use and technological change, but also by long-standing patterns of economic expansion, globalization, and transport-intensive trade. Against this background, this paper makes three contributions. First, it assembles a high-dimensional dataset of 104 macroeconomic and socioeconomic indicators for the EU-27 over the period 1970–2019, substantially expanding the information set typically used in studies of the Ecological Footprint. Second, it proposes a Structural Augmented Dynamic Factor Model to capture latent macroeconomic forces underlying environmental pressure, thereby moving beyond empirical approaches based solely on observable predictors. Third, by comparing non-supervised and supervised factor extraction methods, the analysis identifies two latent macroeconomic drivers, aggregate economic activity and international trade, that have governed the evolution of the European Ecological Footprint over the last five decades.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 presents the methodological framework. Section 4 reports the empirical results. Section 5 discusses the findings and their macroeconomic and policy implications. Section 6 concludes.

2. Data

The dependent variable in this study is the annual per capita Ecological Footprint (EF) of the EU-27, measured in global hectares (gha) per capita and obtained from the Global Footprint Network. The series covers the period 1970–2019, providing a perspective on ecological pressure in Europe. Throughout the analysis, the EU-27 composition is applied retroactively to the entire period to ensure a consistent geographic definition over time, regardless of the dates at which individual countries joined the European Union.

Figure 1 shows the evolution of EF over the sample period. Overall, EF decreases from 5.54 gha per capita in 1970 to 4.62 gha per capita in 2019, although this decline is not monotonic. Before 1990, the series exhibits pronounced fluctuations, with a peak of 5.60 gha in 1979 and a trough of 5.21 gha in 1983. From 1990 to 1993, EF declines steadily, followed by an increase that lasts until 2007, a period likely associated with economic expansion and rising consumption. After 2007, EF falls almost continuously, stabilizing toward the end of the sample. These patterns suggest a close relationship between EF and the economic cycle, especially during major macroeconomic events such as the early-1990s recession and the 2008 financial crisis.

To investigate the socioeconomic determinants of EF, we construct a database of 104 annual variables (Appendix 1) sourced from the World Bank, covering the same period as the EF series. The selection of explanatory variables is crucial in a factor-based framework, since both the number and the nature of the proxies influence the accuracy of latent factor extraction (Bai and Ng, 2002; Watson, 2003; Stock and Watson, 2009; Eickmeier and Ng, 2011). Rather than including the full universe of available macroeconomic indicators, we select variables that have been widely used in the environmental economics and sustainability literature. The database includes indicators related to the business cycle (such as GDP per capita, investment and national income), globalization and international trade, urbanization, demographic structure, population growth and education. These categories capture broad socioeconomic dynamics that may influence ecological pressure at the aggregate level.

Variables directly associated with natural resource extraction or ecological accounting are excluded to avoid mechanical correlations with EF, given that many of these indicators are components of EF calculations. Likewise, although numerous studies document the role of renewable energy in reducing environmental degradation, we do not include renewable energy variables because consistent annual data are only available from 1990 onward. Since our objective is to maintain an analysis spanning five decades, we prioritize temporal consistency at the expense of including these shorter series.

To ensure the statistical adequacy of the time series, all variables, including EF, are transformed to achieve stationarity. When feasible, this is done by applying logarithmic transformation followed by first differencing, which yields growth rates. For variables expressed as rates or containing negative values, only first differencing is applied. Subsequently, all variables are standardized by subtracting their sample mean and dividing by their standard deviation, ensuring comparability across indicators and preventing scale effects from influencing the factor extraction. Although some methodologies allow estimation of DFMs with non-stationary variables, the relatively short annual series used here makes stationarity preferable. Moreover, simulation evidence from Poncela and Ruiz (2016) suggests that factor estimates obtained from stationary transformations are nearly identical to those derived from procedures that explicitly account for non-stationarity.

After preprocessing and standardization, we examine the pairwise correlations between EF and each of the 104 explanatory variables. Table 1 reports the indicators with the highest absolute correlations. Variables typically associated with the business cycle (e.g., adjusted net national income, with a correlation of 0.82, and GDP, 0.77) and international trade (e.g., imports and exports of goods and services, 0.82) rank among the strongest correlates of EF. These initial descriptive results provide a preliminary indication that both economic activity and trade-related dynamics are likely to play significant roles in explaining patterns of ecological pressure in the EU-27.

3. Methods

This section describes the methodological framework used to estimate the relationship between the EF in the EU-27 and a broad set of socioeconomic indicators. We begin by presenting the regression model that combines observable predictors with unobserved latent factors derived from the high-dimensional dataset. We then outline the procedures used to select the most relevant indicators and to extract both non-supervised and supervised common factors.

3.1 Structural Augmented Dynamic Factor Model

Given that the database contains 104 socioeconomic variables but only 50 annual observations, dimensionality reduction is essential for any meaningful econometric analysis. To address this challenge, we follow the Dynamic Factor Model DFM approach, which extracts a small number of latent common factors that summarize the shared variation across the large panel of predictors.

The DFM originates from the seminal work of Geweke (1977), who extended classical factor models to time-series contexts. Subsequent contributions demonstrated that a relatively small set of latent factors can explain a large proportion of macroeconomic variation, particularly in relation to business-cycle dynamics and monetary policy transmission (Sargent and Sims, 1977, Giannone *et al.*, 2004, Stock and Watson, 2016). More recently, DFMs have been applied to environmental topics, including the EF (Delgado-Rodríguez *et al.*, 2021) and CO_2 emissions (Fosten, 2019, Bennedsen *et al.*, 2021, De Juan *et al.*, 2024). Our approach follows this line of research, extending the methodology to measure environmental degradation through EF within the European context. In particular, we consider the following factor-augmented regression model:

$$EF_t = \alpha + \sum_{j=1}^{k} \beta_j^{(x)} x_{i_j t} + \sum_{j=1}^{r} \beta_j^{(f)} F_{jt} + u_t \tag{1}$$

Where $x_{i_j t}$ with $i_j \in \{1, \dots N\}$ and j=1,…k, denotes the subset of observable indicators selected from the database $X_t = (x_{1t}, \dots, x_{Nt})'$. The selection procedure used to obtain these variables is described in the Section 3.3. The term $F_t = (F_{1t}, \dots, F_{rt})'$ represents the r x1 vector of latent common factors extracted from our database X_t., using Principal

Components PC and Partial Least Squares PLS, as detailed in Section 3.2. Finally, u_t is an i.i.d. error term with mean zero and a constant variance. The parameters ${\beta_j}^{(x)}$ and ${\beta_j}^{(f)}$ are estimated by ordinary least squares. When factors are estimated using PC, the resulting least squares estimator is consistent (Stock and Watson, 2002). For PLS, which combines elements of PC and multiple regression, Ahn and Bae (2022) provide the asymptotic properties.

To evaluate the contribution of observable indicators and latent factors, we estimate three restricted versions of equation (1). First, a structural model without latent factors (REG), obtained by imposing ${\beta_j}^{(f)} = 0_{rx1}$. Second, a restricted augmented DFM (R-SADFM) in which only the estimated factors enter the regression, imposing ${\beta_j}^{(x)} = 0$ for all $j = 1, \ldots, k$. Finally, an unrestricted augmented DFM (U-SADFM) that includes both the selected indicators and the latent factors. Comparing these specifications allows us to identify the components with the highest explanatory power for EF dynamics in the EU-27.

3.2. Non-supervised and Supervised Common Factors

To extract common factors from the high-dimensional dataset, we implement two complementary approaches: non-supervised extraction through PC and supervised extraction through PLS.

Following Stock and Watson (2002), we assume that the N variables in X_t are driven by a small number r of latent factors and idiosyncratic disturbances:

$$X_t = \Lambda F_t + \varepsilon_t \tag{2}$$

where F_t is a rx1 vector of latent factors, Λ is the Nxr matrix of factor loadings, and ε_t is an idiosyncratic error vector with mean zero and covariance matrix Σ_ε,, allowing for weak cross-sectional and serial correlation.

Because DFMs are not identified without restrictions, identification requires imposing r^2 constraints. A standard approach assumes that the factors are orthogonal $\left(\frac{F\prime F}{T} = I_r\right)$, providing $\frac{r(r+1)}{2}$ restrictions. The remaining $\frac{r(r-1)}{2}$ restrictions are obtained by assuming that $\Lambda'\Lambda$ is diagonal with distinct elements ordered in descending magnitude. These constraints ensure that the factors are uniquely identified up to a sign normalization. The

PC factors are then computed as the eigenvectors associated with the largest eigenvalues of the sample covariance matrix of X_t.

While PC captures the maximum variance in X_t, it does not consider the prediction target and may therefore produce factors with limited explanatory power for EF. To address this limitation, we also extract supervised factors using PLS, originally introduced by Wold (1966). PLS has been widely used in macroeconomic forecasting and financial applications (Fuentes *et al.*, 2015, Kelly and Pruitt, 2015). Bai and Ng (2008) also propose alternative supervised procedures, although in our empirical setting PLS yields the highest explanatory power.

PLS extracts factors that maximize the covariance between the predictors X and the target variable EF. The method constructs the factors iteratively via the decomposition:

$$M^{(i)} = X^{(i)\prime} EF^{(i)} EF^{(i)\prime} X^{(i)} \qquad with\ i = 1, \ldots, r \tag{3}$$

The first iteration begins with $X^{(i)}$ = X and $EF^{(i)}$ = EF. The first eigenvector of $M^{(i)}$ is used to compute the first factor. For subsequent factors, the method follows Wold (1966): $X^{(i)}$ contains the residuals from regressing all predictors on the previously extracted factor, while $EF^{(i)}$ consists of the residuals from regressing EF on the same factor. his iterative process continues until all r supervised factors are obtained. Loadings for each factor correspond to the correlations between the relevant residual predictors and the extracted factor.

3.3. Selection of Observable Indicators

Since it is not feasible to include all 104 variables as regressors in equation (1), we complement the factor extraction with a variable selection procedure to identify a small set of observable indicators with high explanatory capacity. We employ the Least Absolute Shrinkage and Selection Operator LASSO, introduced by Tibshirani (1996), which performs variable selection by penalizing the absolute magnitude of regression coefficients:

$$\hat{\beta}_{LASSO} = \mathrm{argmin}_{\beta} \left\{ \sum_{i=1}^{N} \left(\tilde{y}_i - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{4}$$

Where $\tilde{Y} = Y - \bar{y}1_n$ and $\lambda \geq 0$ is the regularization parameter.. If $\lambda = 0$, LASSO reduces to OLS, whereas large λ values shrink all coefficients toward zero. An optimal value of λ is typically chosen to balance fit and parsimony. Applying LASSO to our dataset under various values of λ, we select λ=3 because it yields stable and interpretable results. The selected indicators are gross capital formation, imports of goods and services and adjusted net national income, which emerge as the variables most strongly associated with EF.

4. Results

This section presents the empirical results obtained using the methods introduced in Section 3. It is structured into two subsections. Section 4.1 examines the extraction and interpretation of the non-supervised and supervised common factors derived from the high-dimensional dataset. Section 4.2 evaluates the performance of the different model specifications, identifying those with the highest capacity to explain the evolution of the EF.

4.1 Non-supervised and Supervised Common Factors

The selection of the optimal number of factors is a central issue in Dynamic Factor Model (DFM) analysis. Several criteria have been developed for this purpose, with those proposed by Bai and Ng (2002), Onatski (2010) and Alessi *et al.* (2010) being among the most widely used. When we initially allow for a maximum of 20 factors, most criteria suggest retaining four factors (r = 4). However, closer inspection reveals that the third and fourth factors are essentially linear combinations of the first two, and they do not exhibit statistical significance when included in the model estimations. Given the moderate size of our database (104 socioeconomic variables), we restrict the maximum number of factors to four and recalculate the criteria. Under this restricted setting, the optimal number of factors is two (r = 2), which jointly explain 30.27% of the variance of the standardized dataset Xt. We adopt this specification.

The first non-supervised factor extracted using Principal Components (PC) accounts for 19.52% of the total variance in Xt. Figure 2.1 shows the variables with the largest absolute loadings. These correspond to indicators typically associated with the business cycle, such as GDP per capita, Gross National Expenditure and Gross Capital Formation. Most of these variables load positively on the factor, indicating that increases in the factor align with expansions in procyclical economic indicators. In contrast, variables such as spending on food, services and education load negatively, suggesting that these components tend to behave countercyclically. This finding is consistent with the notion that expenditure on essential goods is maintained or increased during recessions.

The second non-supervised factor explains 10.75% of the variance and is primarily associated with different components of international trade. As shown in Figure 2.2, variables such as goods imported from developing economies outside the region, trade with Central Asia, and trade with the Middle East and Africa have strongly positive loadings. By contrast, imports and exports from high-income economies, as well as manufactured goods, load negatively. This pattern suggests that trade involving longer distances and more transport-intensive flows contributes positively to the factor, whereas trade with advanced economies is associated with an opposite dynamic.

When extracting factors using Partial Least Squares (PLS), the resulting structure is broadly consistent with that obtained through PC. The indicators with the highest positive loadings in the first supervised factor include GDP per capita, National Expenditure, Gross Capital Formation and National Income, all of which strongly reflect the European business cycle. The second supervised factor is dominated by variables linked to international trade, particularly with developing regions such as Central Asia, Latin America, the Caribbean and South Asia. Thus, both PC and PLS capture the same two underlying economic forces, although the supervised approach yields factors that are more tightly connected with the evolution of EF.

Crucially, the supervised factors exhibit substantially greater explanatory power. The two supervised factors jointly explain approximately 84.5% of the variance in EF, 73.5% attributable to the first factor and 11% to the second, far outperforming the non-supervised factors. Because PLS maximizes covariance with EF, the resulting factors are inherently more aligned with environmental dynamics. This result confirms the advantage of supervised factor extraction when the aim is to identify socioeconomic forces most closely associated with environmental degradation.

Figures 3.1 and 3.2 illustrate the temporal evolution of the non-supervised and supervised factors. The first pair of factors follows a similar trajectory and provides an excellent representation of European economic activity. However, notable differences emerge around the early 1990s and during the 2008 financial crisis: in 1992, the non-supervised factor reaches a lower trough than the supervised one, while in 2008 the supervised factor exhibits a sharper decline and a stronger recovery. The second pair of factors also aligns with broad economic trends but displays more fluctuations, reflecting the sensitivity of international trade to global conditions. During recessionary periods, negative peaks are less pronounced, possibly due to the increased price competitiveness of European exports to developing economies.

Finally, Table 3 reports the correlations among the extracted factors, the dependent variable and the factors themselves. The first factor, both supervised and non-supervised, is strongly correlated with EF, which is consistent with the role of the business cycle in shaping ecological pressure. The correlation between the supervised and non-supervised versions of this factor is high (0.98), reflecting their similar economic interpretation. The second factor displays moderate correlation with EF in its supervised version (0.33) but virtually no correlation in its non-supervised version (0.21), highlighting the value added by supervised estimation. Overall, the results indicate a strong connection between EF, economic activity and international trade.

4.2 Model Specification

We now evaluate the performance of the different model specifications introduced in Section 3. The first specification includes only the three predictors selected using the LASSO procedure REG. The second set consists of two reduced Structural Augmented Dynamic Factor Models R-SADFM that rely solely on the extracted factors, one using PC factors and the other using PLS factors. Finally, the unrestricted models U-SADFM incorporate both the LASSO-selected indicators and the extracted factors.

The results, reported in Table 4, indicate that the model with the highest explanatory power is the R-SADFM estimated with the two supervised factors, which achieves an R^2 of approximately 85 percent. This performance exceeds that of the models based on PC factors, a result consistent with the literature on supervised factor extraction (De Juan *et al.*, 2024). Including the LASSO-selected variables does not improve model performance, as these variables are not statistically relevant once the factors are included. This finding supports selecting the supervised-factor specification as the preferred model for explaining EF dynamics.

Finally, we should note that the estimated coefficients for the supervised factors reveal positive and statistically significant effects, in particular the estimation of $\hat{\beta}_{fpls1}$ takes the value 5.87, whilst the estimation of $\hat{\beta}_{fpls2}$ is 2.30. To assess the stability of these effects over time, we conduct a rolling-window estimation using recursive methods. The results suggest that the coefficients remain stable throughout the sample period, indicating robust and persistent relationships between EF, macroeconomic activity and international trade (Appendix 2).

5. Discussion

The empirical results reveal that the long-term evolution of the EF in the EU-27 is governed by two persistent and structurally influential forces: the dynamics of aggregate economic activity and the configuration of international trade. The strong and positive association between EF and the business cycle is consistent with a wide body of evidence showing that environmental pressures intensify during economic expansions (Sun *et al.*, 2022). Similar patterns documented for CO_2 emissions and broader GHG indicators (Gaies *et al.*, 2022), as well as for other geographic regions (Magazzino, 2024; Asif *et al.*, 2024), suggest that the procyclicality of environmental degradation is a global rather than regional phenomenon. A key contribution of this study is that the relationship is captured not only through observable variables, such as GDP per capita or investment, but through a latent macroeconomic force extracted using supervised factor techniques. This indicates that the link between environmental degradation and economic activity is embedded in deep structural dynamics that go beyond conventional macroeconomic indicators.

The second major result concerns the role of international trade. While numerous studies argue that trade openness contributes to environmental degradation, particularly via increased EF (Eweade *et al.*, 2023; Zambrano-Monserrate *et al.*, 2020; Ali *et al*., 2021), the factor structure uncovered in this study allows us to identify the underlying channels. The supervised trade factor is shaped by variables reflecting long-distance trade, exchanges with developing economies and trade in manufactured goods—precisely the components most closely associated with embodied emissions and transport-related environmental impacts. This interpretation aligns with extensive research on emission transfers and global value chains, which shows that a growing share of environmental pressure in developed economies is effectively “imported” through trade (Davis and Caldeira, 2010; Peters *et al.*, 2011; Wiedmann and Lenzen, 2018). Transport itself is an additional mechanism: freight activity accounts for a substantial portion of European GHG emissions (EEA, 2022), reinforcing the link between trade intensity and EF.

A central methodological implication emerges from the finding that supervised factors explain a significantly larger proportion of EF variance than non-supervised factors. Because PLS maximizes covariance with the dependent variable, the resulting factors are inherently more aligned with environmental dynamics. This validates the use of supervised factor extraction in environmental macroeconomics and highlights the advantage of combining high-dimensional datasets with factor-based modelling when analyzing complex environmental indicators such as EF.

These results carry important policy implications. First, the persistent coupling between the business cycle and environmental degradation underscores the need for structural forms of green growth, rather than policies targeting isolated sectors or variables. Evidence of partial decoupling in some European countries (Baigorri *et al.,* 2025; Wang *et al.,* 2023) suggests that technological innovation, renewable energy adoption and efficiency improvements can reduce ecological pressure, but these strategies must be strengthened to counteract the cyclical forces identified in this study. Second, the environmental consequences of trade call for strategies aimed at restructuring supply chains, promoting more localized production systems, improving logistics efficiency and reducing emissions embedded in traded goods. Measures such as multimodal freight transport, carbon-efficient shipping and incentives for proximity-based commerce (Coscieme *et al.*, 2020; Steffen *et al.,* 2015) could substantially decrease EF while supporting economic competitiveness.

Taken together, the findings offer evidence that environmental degradation in Europe is not solely driven by sectoral activity or consumption patterns but is deeply rooted in macroeconomic and trade structures. Addressing these forces is essential for achieving long-term environmental sustainability.

6. Conclusion

This paper analyses the determinants of the Ecological Footprint in the EU-27 over the period 1970–2019 using a high-dimensional socioeconomic database and a Dynamic Factor Model framework combining non-supervised and supervised factor extraction with LASSO-based variable selection. The results show that two latent structural forces, the business cycle and international trade, consistently explain movements in EF. The supervised factors, derived through Partial Least Squares, demonstrate particularly strong explanatory power, accounting for 84.5% of EF variance. This highlights the relevance of supervised factor extraction methods for environmental macroeconomic analysis and shows that ecological degradation is shaped by broad macroeconomic and trade dynamics rather than by isolated observable indicators.

The findings suggest that achieving environmental sustainability in Europe will require addressing the structural coupling between economic activity, trade intensity and ecological pressure. Policies promoting low-carbon growth, renewable energy deployment, technological innovation and resource efficiency are essential to mitigate the procyclical behavior of environmental degradation. Likewise, reconfiguring trade structures towards shorter, less transport-intensive supply chains, improving freight transport sustainability and reducing embodied emissions in imports can play a central role in lowering the EF. These strategies are aligned with the objectives of the European Green Deal and reinforce the need for systemic and long-term transformations rather than incremental adjustments.

This study also has limitations arising from data availability, including the exclusion of renewable energy variables over the full period and the omission of 2020 due to distortions from the COVID-19 shock. Future research could extend the analysis to the post-pandemic period, incorporate structural breaks or regime changes, and explore country-level heterogeneity within the EU-27 to better inform national policy design.

Overall, the paper contributes to the literature by providing new evidence on the structural determinants of ecological pressure in Europe and by demonstrating the value of supervised factor extraction in environmental analysis. The results underscore the importance of addressing the macroeconomic and trade forces that drive ecological degradation if the EU is to achieve long-term environmental sustainability.

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TABLES

Table 1. Pairwise correlation coefficients between the EF and the explanatory variables.

	EF
Adjusted net national income (constant 2010 US$)	0.821
Imports of goods and services (constant 2010 US$)	0.819
Gross capital formation (constant 2010 US$)	0.813
Gross national expenditure (constant 2010 US$)	0.802
GDP per capita (constant 2010 US$)	0.773
GDP (constant 2010 US$)	0.764
Gross value added at factor cost (constant 2010 US$)	0.740
Gross fixed capital formation (constant 2010 US$)	0.690
Final consumption expenditure by households (constant 2010 US$)	0.659
Exports of goods and services (constant 2010 US$)	0.647
Gross domestic savings (% of GDP)	0.637
Adjusted savings: consumption of fixed capital (% of GNI)	-0.621
Merchandise imports (current US$)	0.575
Merchandise imported by the reporting economy (current US$)	0.570
Final consumption expenditure (constant 2010 US$)	0.562
Merchandise exports (current US$)	0.559
Merchandise exported by the reporting economy (current US$)	0.556
Imports of minerals and metals (% of merchandise imports)	0.545
Adjusted savings: education expenditure (% of GNI)	-0.544
Merchandise exports to developing economies outside the region (% of total merchandise exports)	-0.523

This table reports the variables within the database most correlated (positively or negatively) with the Ecological Footprint. Only correlations with an absolute value greater than 0.50 are shown.

Table 2: Variables selected through the LASSO procedure

Maxvar	Q1	Q2	Q3	Q4
2	Imports of goods and services			Imports of goods and services
	Adjusted net national income			Adjusted net national income
3	Gross capital formation		Gross capital formation	Gross capital formation
	Imports of goods and services		Imports of goods and services	Imports of goods and services
	Adjusted net national income		Adjusted net national income	Adjusted net national income
4	Adjusted savings: consumption of fixed capital	Gross capital formation	Gross capital formation	Adjusted savings: consumption of fixed capital
	Gross capital formation	Gross national expenditure	Gross national expenditure	Gross capital formation
	Imports of goods and services	Imports of goods and services	Imports of goods and services	Imports of goods and services
	Adjusted net national income	Adjusted net national income	Adjusted net national income	Adjusted net national income

Table shows the variables selected by LASSO under different penalty schemes: Q1 pure L1, Q2 75% L1 – 25% L2, Q3 50% L1 – 50% L2, and Q4 pure L2. The first column indicates the maximum number of variables allowed. Empty cells indicate that no variables were selected under that scheme.

Table 3: Pairwise correlation among EF and the extracted factors

	EF	f1	f2	fpls1	fpls2
EF	1.00				
f1	0.80	1.00			
f2	0.21	0.00	1.00		
fpls1	0.85	0.98	0.14	1.00	
fpls2	0.33	-0.16	0.68	0.00	1.000

This table displays the Pearson correlation coefficients between EF and each of the latent factors, as well as the correlations among the supervised and non-supervised factors themselves.

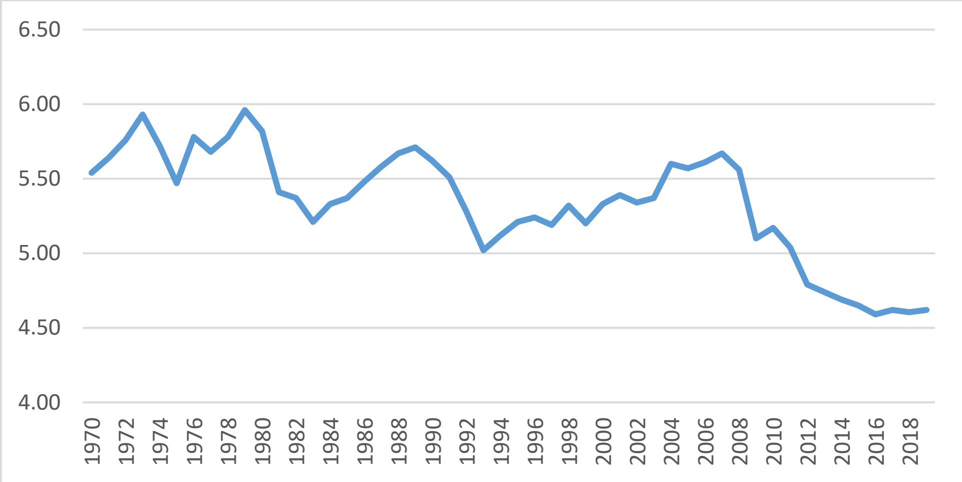
Table 4: Estimation results for the different model specifications

Model	$\hat{\alpha}$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_{fpc1}$	$\hat{\beta}_{fpc2}$	$\hat{\beta}_{fpls1}$	$\hat{\beta}_{fpls2}$	R^2
REG	0.00	0.12	0.36	0.41					0.73
	(0.07)	(0.55)	(1.83)	(2.64)					
R-SADFM$_{PC}$	0.00				0.80	0.21			0.68
	(0.08)				(9.61)	(2.55)			
U-SADFM$_{PC}$	0.00	0.12	0.36	0.41	-0.005	-0.005			0.73
	(0.78)	(0.10)	(1.48)	(1.79)	(-0.02)	(-0.04)			
R-SADFM$_{PLS}$	0.00						5.87	2.30	0.85
	(0.05)						(14.73)	(5.77)	
U-SADFM$_{PLS}$	0.00	-0.38	0.25	-0.20			7.93	2.82	0.86
	(0.55)	(-2.04)	(1.56)	(-1.29)			(4.44)	(6.19)	

This table reports the estimated parameters and explanatory power (R^2) of all considered models. REG includes only the variables selected via LASSO. R-SADFM includes only the extracted factors, while U-SADFM includes both the selected variables and the extracted factors. Factors are estimated either by Principal Components (PC) or Partial Least Squares (PLS).

FIGURES

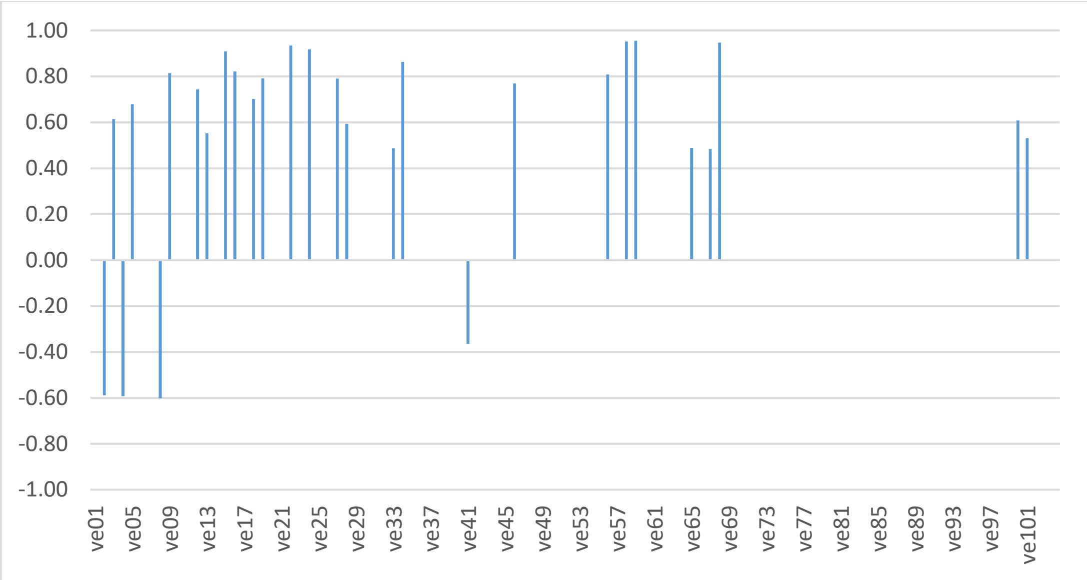
Figure 1. Evolution of the Ecological Footprint per capita, 1970–2019



The series is expressed in real terms prior to normalization and standardization.

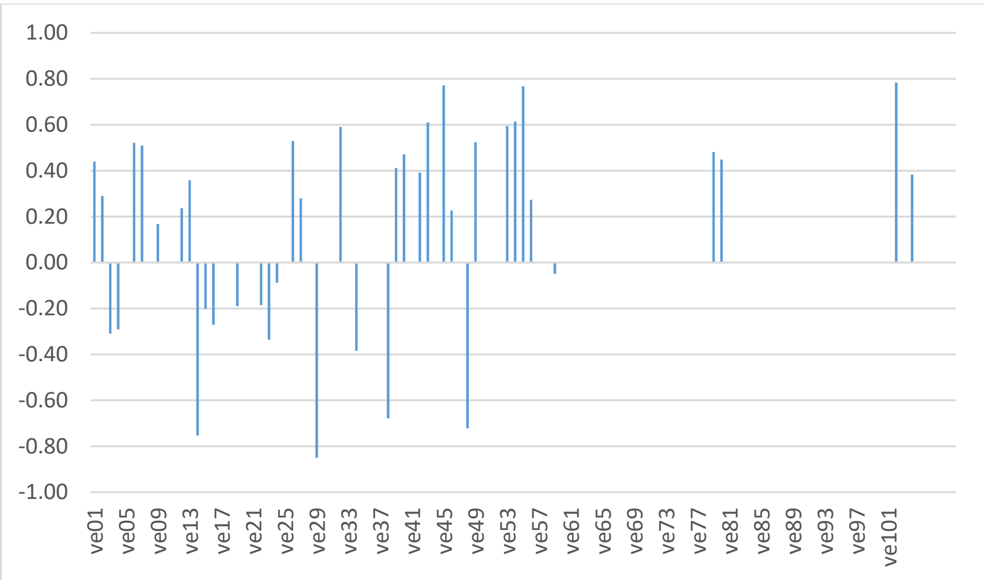
Figure 2. Estimated Loadings

Figure 2.1 Estimated loadings of non-supervised factor 1



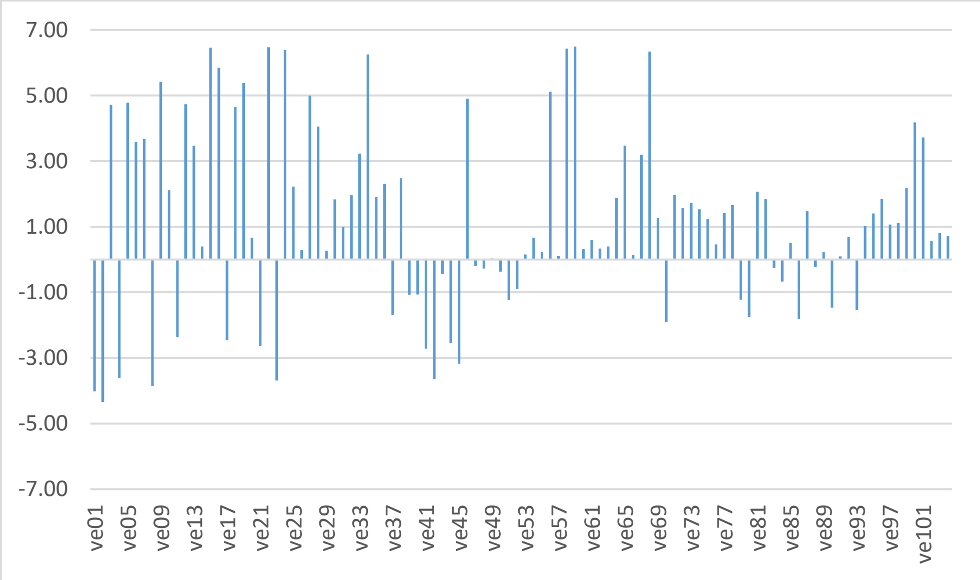
This figure shows the variables with loadings significantly different from zero at the 5% level. Significance is assessed using the asymptotic variance of Bai (2003).

Figure 2.2. Estimated loadings of non-supervised factor 2



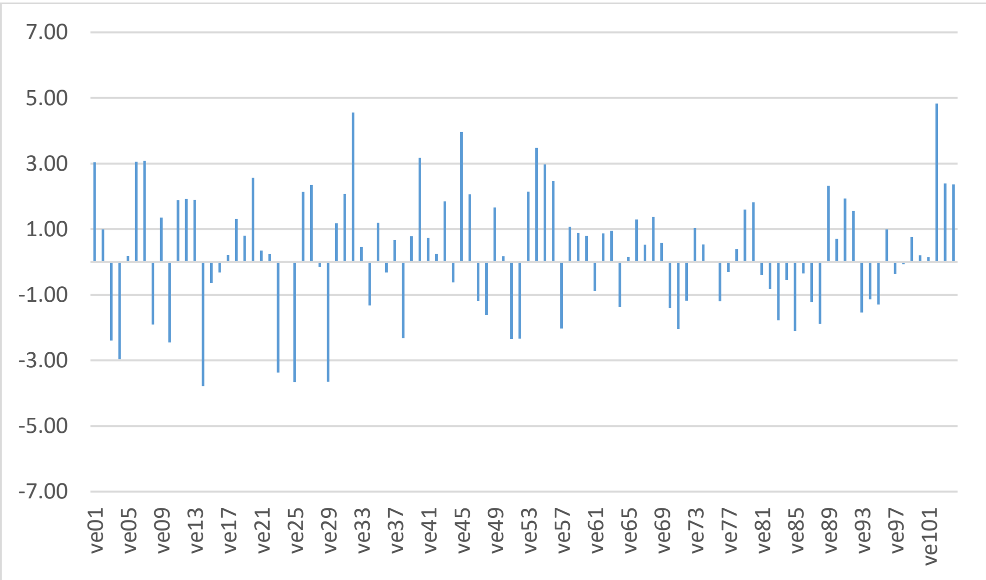
This figure shows the variables with loadings significantly different from zero at the 5% level. Significance is assessed using the asymptotic variance of Bai (2003).

Figure 2.3. Estimated loadings of supervised factor 1



This graph shows the factor 1 loadings for each of the variables in the database. The variables with the highest loadings are related to the economic cycle.

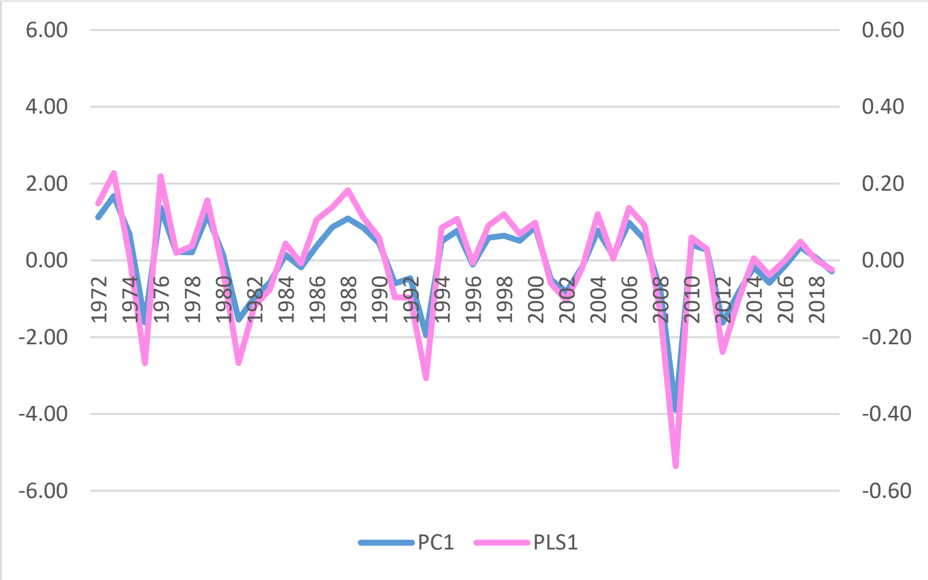
Figure 2.4 Estimated loadings of supervised factor 2



This graph shows the factor 2 loadings for each of the variables in the database. The variables with the highest loadings are related to the international trade.

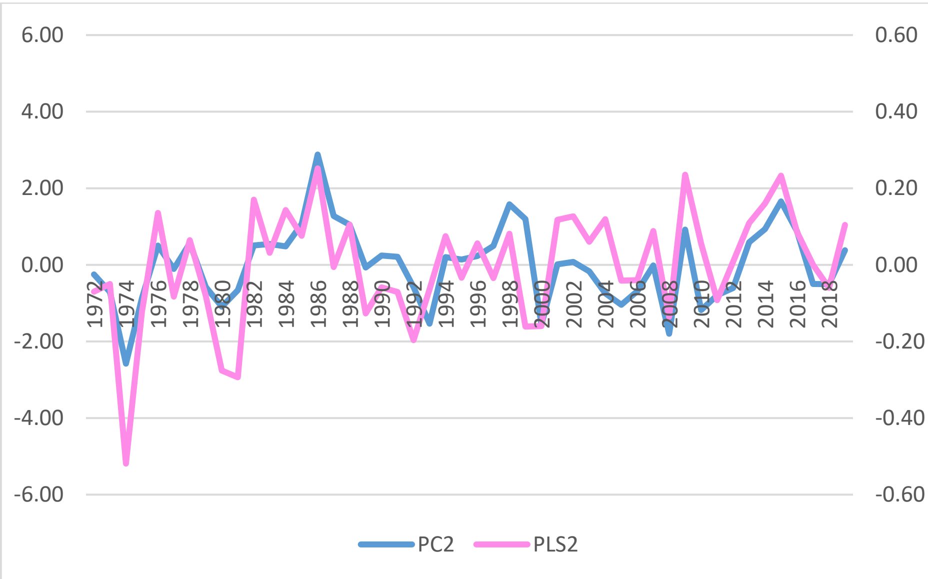
Figure 3. Estimated common factors

Figure 3.1 Non- supervised and supervised factor 1



This figure plots the evolution of the first common factor. The left axis corresponds to the non-supervised factor extracted via Principal Components, and the right axis to the supervised factor extracted via Partial Least Squares.

Figure 3.2 Non- supervised and Supervised -factor 2



This figure plots the evolution of the first common factor. The left axis corresponds to the non-supervised factor extracted via Principal Components, and the right axis to the supervised factor extracted via Partial Least Squares.

APPENDIX

Appendix 1: List of 104 variables

ve01 Adjusted savings: consumption of fixed capital (% of GNI)

ve02 Adjusted savings: education expenditure (% of GNI)

ve03 Gross domestic savings (% of GDP)

ve04 Trade balance of goods and services (% of GDP)

ve05 Net financing capacity (+)/net financing need (-) (% of GDP)

ve06 Trade (% of GDP)

ve07 Merchandise trade (% of GDP)

ve08 Food exports (% of merchandise exports)

ve09 Exports of goods and services (constant 2010 US$)

ve10Agricultural raw material exports (% of merchandise exports)

ve11 Merchandise exports to Arab world economies (% of total merchandise exports)

ve12 Merchandise exports (current US$)

ve13 Metal and mineral exports (% of merchandise exports)

ve14 Manufactured goods exports (% of merchandise exports)

ve15 Gross capital formation (constant 2010 US$)

ve16 Gross fixed capital formation (constant 2010 US$)

ve17 Expenditure (% of GDP)

ve18 Final consumption expenditure (constant 2010 US$)

ve19Household final consumption expenditure (constant 2010 US$)

ve20General government final consumption expenditure (constant 2010 US$)

ve21Military expenditure (% of GDP)

ve22 Gross national expenditure (constant 2010 US$)

ve23 Food imports (% of merchandise imports)

ve24 Imports of goods and services (constant 2010 US$)

ve25 Agricultural raw material imports (% of merchandise imports)

ve26 Merchandise imports from Arab world economies (% of total merchandise imports)

ve27 Merchandise imports (current US$)

ve28 Metal and mineral imports (% of merchandise imports)

ve29 Manufactured goods imports (% of merchandise imports)

ve30 Taxes on income, profits, and capital gains (% of revenue) ve31 Inflation, GDP deflator (% annual)

ve32 Inflation, consumer prices (% annual)

ve33 Gross national income (GNI) (US$)

ve34 Adjusted net national income (constant 2010 US$)

ve35 Foreign direct investment, net inflows (BoP, current US$)

ve36 Foreign direct investment, net outflows (BoP, current US$)

ve37 Portfolio investment, net inflows (BoP, current US$)

ve38 Merchandise exports to high-income economies (% of total merchandise exports)

ve39 Merchandise exports to developing economies in Sub-Saharan Africa (% of total merchandise exports)

ve40 Merchandise exports to developing economies in Latin America & Caribbean (% of total merchandise exports)

ve41 Merchandise exports to developing economies in South Asia (% of total merchandise exports)

ve42 Merchandise exports to developing economies in East Asia & Pacific (% of total merchandise exports)

ve43 Merchandise exports to developing economies in Europe & Central Asia (% of total merchandise exports)

ve44 Merchandise exports to developing economies in Middle East & North Africa (% of total merchandise exports)

Ve45Merchandise exports to developing economies outside the region (% of total merchandise exports)

ve46 Merchandise exports by reporting economy (current US$)

ve47 Merchandise exports by reporting economy, surplus (% of total merchandise exports)

ve48 Merchandise imports from high-income economies (% of total merchandise imports)

ve49 Merchandise imports from developing economies in Sub-Saharan Africa (% of total merchandise imports)

ve50 Merchandise imports from developing economies in Latin America & Caribbean (% of total merchandise imports)

ve51 Merchandise imports from developing economies in South Asia (% of total merchandise imports)

ve52 Merchandise imports from developing economies in East Asia & Pacific (% of total merchandise imports)

ve53 Merchandise imports from developing economies in Europe & Central Asia (% of total merchandise imports)
ve54 Merchandise imports from developing economies in Middle East & North Africa (% of total merchandise imports)
ve55 Merchandise imports from developing economies outside the region (% of total merchandise imports)
ve56 Merchandise imports by reporting economy (current US$)
ve57 Merchandise imports by reporting economy, surplus (% of total merchandise imports)
ve58 GDP (constant 2010 US$)
ve59 GDP per capita (constant 2010 US$)
ve60 Aquaculture production (metric tonnes)
ve61 Cereal production (metric tonnes)
ve62 Capture fisheries production (metric tonnes)
ve63 Total fishery production (metric tonnes)
ve64 Water productivity, total (GDP in constant 2010 US$ per metre of water)
ve65 Tax revenue (% of GDP)
ve66 Revenue, excluding grants (% of GDP)
ve67 Gross value added at factor cost (current US$)
ve68 Gross value added at factor cost (constant 2010 US$)
ve69 Workers' remittances and compensation of employees, paid (current US$)
ve70 Fertiliser consumption (% of fertiliser production)
ve71 Fertiliser consumption (kilograms per hectare of arable land)
ve72 Population density (people per square km)
ve73 Life expectancy at birth, female (years)
ve74 Life expectancy at birth, total (years)
ve75 Life expectancy at birth, male (years)
ve76 Population ages 65 and above, male (% of total)
ve77 Population ages 65 and above, female (% of total)
ve78 Population ages 65 and above, total
ve79 Population ages 70-74, female (% of female population)
ve80 Population ages 70-74, male (% of male population)
ve81 Population ages 75-79, female (% of female population)
ve82 Population ages 75-79, male (% of male population)

ve83 Population in the largest city (% of urban population)

ve84 Population in urban agglomerations >1 million (% of total population)

ve85 Fertility rate, total (births per woman)

ve86 Death rate, annual (per 1,000 people)

ve87 Birth rate, annual (per 1,000 people)

ve88 Primary education, students enrolled

ve89 Secondary education, students enrolled

ve90 Ratio of female to male enrollment in primary education (%)

ve91 Ratio of female to male enrollment in secondary education (%)

ve92 Ratio of female to male enrollment in tertiary education (%)

ve93 Primary school repeaters, total (% of total enrollment)

ve94 Primary education completion rate, female (% of relevant age group)

ve95 Primary education completion rate, male (% of relevant age group)

ve96 Lower secondary education completion rate, total (% of relevant age group)

ve97 Charges for intellectual property use, payments (BoP, current US$)

ve98 Charges for intellectual property use, receipts (BoP, current US$)

ve99 Air transport, freight (million ton-km)

ve100 Air transport, passengers carried

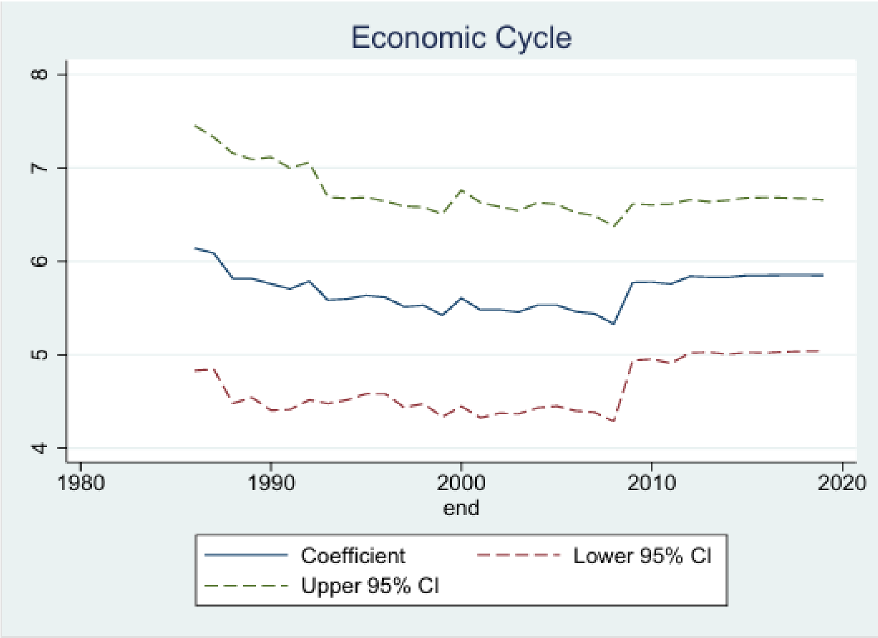
ve101 Air transport, registered carrier departures worldwide

ve102 Adjusted savings: energy depletion (% of GNI)

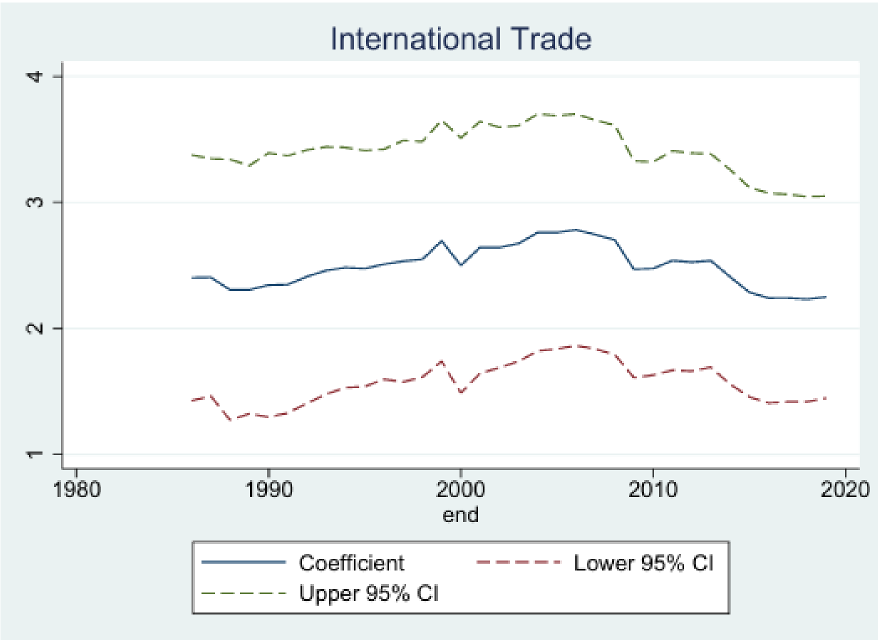
ve103 Urban Population

ve104 Urban Population (% of total population)

Appendix 2: Constant parameters throughout the analyzed period



Evolution of the β_1 coefficient estimated through a recursive procedure. The estimation begins with a fixed 15-year window and, in each iteration, the window is expanded by adding one additional year. The chart displays the estimated values of β_1 from 1986 onward, showing how the parameter evolves as more data become available.



Evolution of the β_2 coefficient estimated through a recursive procedure. The estimation begins with a fixed 15-year window and, in each iteration, the window is expanded by adding one additional year. The chart displays the estimated values of β_2 from 1986 onward, showing how the parameter evolves as more data become available.