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Social Macroeconomic Imbalance Procedure (MIP) Indicators: Do They Matter?

Jacek Karwowski https://orcid.org/0000-0003-2754-5003
Professor, Wroclaw University of Economics and Business, Wroclaw, Poland, e-mail: jacek.karwowski@ue.wroc.pl

Krzysztof Biegun https://orcid.org/0000-0002-4888-6600
Ph.D., Wroclaw University of Economics and Business, Wroclaw, Poland, e-mail: krzysztof.biegun@ue.wroc.pl

Abstract

The European Union's (EU's) Macroeconomic Imbalance Procedure (MIP) increasingly incorporates social indicators alongside traditional economic metrics, yet the empirical relationship between these dimensions remains underexplored. This study investigates whether social outcomes captured by the MIP scoreboard function as independent early-warning signals or merely reflect underlying macroeconomic conditions already monitored through non-social indicators. Analysing panel data for all 27 EU member states over 2001–2023, we employ LASSO regression for variable selection, two-stage fixed-effects estimation, and random forest analysis, validating results through Leave-One-Country-Out Cross-Validation. The findings reveal a fundamental dichotomy. Unemployment is robustly predicted by macro-financial variables, particularly non-performing loans and nominal unit labour costs, a result consistent across all three methods. In contrast, post-transfer poverty rates prove unpredictable from macroeconomic conditions regardless of model specification, suggesting that redistribution outcomes are decoupled from macro-financial variables and may be influenced by national tax-and-benefit systems not captured in the MIP scoreboard. Labour force participation similarly shows no significant association with any non-social indicator. We propose a dual-track reform: streamlining the MIP to focus on macroeconomic surveillance while establishing a parallel Social Convergence Framework for redistribution policy monitoring. Macroeconomic stability remains necessary for social progress across EU member states, but it does not account for poverty outcomes that appear linked to national social policies beyond the MIP's scope.

Keywords: Macroeconomic Imbalance Procedure, social indicators, unemployment, poverty, European Semester, EU economic governance, Social Convergence Framework

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Introduction

The global financial crisis of 2008 and the euro area sovereign debt crisis that followed exposed critical gaps in the European Union's (EU's) economic governance architecture. While fiscal rules had long been in place through the Stability and Growth Pact, no comparable mechanism existed for the early detection of broader macroeconomic risks such as excessive credit growth, unsustainable property price increases, or persistent current account deficits that could destabilise individual member states or the Economic and Monetary Union (EMU) as a whole. In response, the EU introduced the Macroeconomic Imbalance Procedure (MIP) in 2011 as part of the Six-Pack legislative package (European Parliament and Council of the European Union 2011). The MIP is designed to identify, prevent, and address potentially harmful macroeconomic imbalances within member states through a scoreboard of quantitative indicators. The scoreboard findings feed into the annual Alert Mechanism Report (AMR) and, where risks are identified, trigger In-Depth Reviews (IDRs) of individual countries. The MIP operates as a part of the European Semester, the Union's annual cycle of economic and fiscal policy coordination, in which the European Commission evaluates member states' budgetary plans, structural reforms, and macroeconomic developments.

The MIP scoreboard initially focused on "hard" macroeconomic indicators, e.g., current account balance, competitiveness, and debt measures (Franco and Zollino 2014:590–591), but over time, social indicators were also included. Since 2014, the scoreboard has incorporated certain labour market and poverty-related variables in recognition that macroeconomic imbalances often have social consequences. As of 2025, the MIP framework comprises 13 main indicators (of which two are explicitly social – unemployment rate and labour force participation rate, each with defined threshold values), and 23 auxiliary indicators (eight of which cover social domains without formal thresholds). These social MIP indicators track issues like unemployment (especially youth and long-term unemployment) and poverty (material deprivation, low work intensity households, and at-risk-of-poverty rates). However, despite their inclusion, social indicators have remained secondary in the MIP's implementation, which largely prioritises macroeconomic and financial stability concerns (Bricongne, Garcia, and Turrini 2019:3–4; Bacchini, Ruggeri Cannata, and Donà 2020:471; Roblek and Kejžar 2025).

In parallel to the evolution of the MIP, the EU proposed a Social Imbalances Procedure (SIP) in 2017 (Sabato, Vanhercke, and Guio 2022:22). While the SIP was intended to ensure that economic stability would not compromise social cohesion, it has since evolved into the Social Convergence Framework (SCF), officially integrated into the European Semester. The SCF utilises a two-stage analysis: the first identifies risks to upward social convergence via the Social Scoreboard in the Joint Employment Report (JER), while the second provides a deep-dive into specific Member States (e.g., ten countries in 2025). Although social indicators are now more rigorously monitored through this framework, they primarily inform policy coordination rather than triggering the strong enforcement or corrective actions characteristic of the MIP. Consequently, the JER remains the central instrument for assessing progress towards the European Pillar of Social Rights and formulating country-specific recommendations.

This context raises a critical governance question: do social MIP indicators contain incremental diagnostic information once the non-social scoreboard is taken into account, and how should they be interpreted within surveillance – as potential drivers, amplifiers, or primarily outcome indicators of macro-financial developments? Importantly, informational overlap is not, by itself, a sufficient argument for removing an indicator from the MIP surveillance framework (scoreboard), especially when causal ordering is not identified. We therefore assess redundancy in a predictive/informational sense, asking whether social indicators add incremental diagnostic content beyond the non-social block. In governance terms, both weak linkages (suggesting structural decoupling and a distinct policy regime) and strong linkages (suggesting informational redundancy) may motivate relocating social indicators from the MIP scoreboard to a dedicated social monitoring pillar rather than "dropping" them altogether.

This article contributes to this debate by empirically evaluating the relationships between the social MIP variables and the non-social MIP variables. We assess whether deteriorations in social outcomes are systematically associated with developments in the non-social MIP indicators and whether the macro-financial block contains predictive content for social variables, without making causal claims about drivers versus outcomes.

Despite the importance of this issue for European social policy, to the best of our knowledge, no prior research has focused specifically on incremental diagnostic/predictive information of social MIP conditional on the non-social block. We address this gap by analysing a panel dataset covering all EU member states over the past two decades (2001–2023). Using several complementary quantitative methods, we test whether developments in twenty-six non-social MIP indicators contain incremental predictive content for changes in ten selected social indicators, without making causal claims. We thus treat the social indicators as dependent variables and examine their linkages to macroeconomic variables that the European Commission monitors for macroeconomic imbalance detection. In addition, we conduct random forest feature importance analyses to explore the relative significance of different macroeconomic variables in predicting social outcomes.

The novelty of this paper lies in its systematic empirical assessment of whether social indicators provide incremental information beyond the non-social scoreboard for imbalance surveillance, or whether they largely reflect the same underlying macro-financial information set while remaining relevant as welfare and distributional outcome measures.

Although the JER provides a rich analysis of the socio-employment situation, this article focuses exclusively on the MIP because it is the EU's primary mechanism for the surveillance and correction of imbalances, possessing potential enforcement mechanisms. This makes the role of social indicators within its framework a particularly critical issue from the perspective of economic governance.

In the remainder of the paper, we first review the relevant literature and theoretical expectations regarding macroeconomic and social imbalances. Next, we describe our data sources and methodology, which combines a LASSO-based variable selection approach, a two-stage selection procedure with univariate pre-screening and multivariate fixed-effects estimation, and random forest analysis, and we assess predictive performance using out-of-sample Leave-One-Country-Out Cross-Validation (LOCO-CV), a variant designed for grouped panel data. We then present the results of our empirical analysis and discuss their implications for EU policy. Finally, we conclude with reflections on whether the European Semester's current toolkit is adequate for addressing social imbalances or if reforms (such as a dedicated social monitoring procedure) are warranted.

Literature Review

Academic assessments of the MIP can be grouped into two broad strands (Domonkos et al. 2017:R35). The first strand examines the institutional and political dimensions of the MIP – its legal design, implementation, and the willingness of Member States to comply with recommendations. The second strand evaluates the empirical performance of the MIP's indicators, especially their ability to predict crises or signal vulnerabilities. Our study connects most closely with the second strand, as we are concerned with how indicators relate to one another and to socioeconomic outcomes.

Research on early warning systems has employed various definitions of "crisis". For example, some researchers define a crisis by a substantial drop in output (GDP) coupled with a surge in unemployment (Mishkin 2011:22). Others define crisis episodes when an indicator like the output gap or GDP growth deviates markedly from its trend (Harding and Pagan 2002; Domonkos et al. 2017:R36; Siranova and Radvanský 2018:341). Biegun and Karwowski (2020:15–17) introduced the concept of a "multidimensional crisis" based on several economic indicators, such as the decline in GDP, inflation, currency depreciation, stock market decline, and restrictions on cash withdrawals. This approach allowed them not only to identify crises but also to classify their severity.

Given these differing definitions, studies have sometimes reached divergent conclusions regarding which MIP scoreboard indicators are the most effective early warnings of trouble. The Joint Research Centre reviewed these papers and found varying results (Erhart, Becker, and Saisana 2018:28–29). Knedlik (2014:162–163) concluded that the current account, net international investment position, and nominal unit labour costs were the most useful predictors of a debt crisis. Boysen-Hogrefe et al. (2015:10–11) found that private sector credit flow, house prices, and private sector debt were the best indicators of future crises.

These findings align with earlier work on financial crises: Kaminsky (1999:16–17) identified several indicators of financial crises, including growth slowdown, loose monetary policy, overborrowing, bank runs, and balance of payments problems. Borio and Drehmann (2009:35–44) demonstrated that credit-to-GDP, equity, and property price gaps are able to detect the build-up of risks of upcoming banking distress. Sohn and Park (2016:195–198) found that credit growth is more informative in predicting banking crises than the credit-to-GDP gap, findings later confirmed by Geršl and Jašová (2018:27–30). Biegun and Karwowski (2020:20–22) identified five MIP variables that were statistically significant in predicting "multidimensional crises" for all EU countries: net international investment position, nominal unit labour cost index, house price index, private sector credit flow, and general government gross debt.

While significant research has focused on the economic and financial indicators in the MIP, the social indicators have received considerably less scholarly attention. Social variables like unemployment often appear in early warning studies as contributors to crises (e.g., rising joblessness as a symptom of an ongoing crisis) rather than as indicators to be explained. Among the early warning analyses, unemployment itself is sometimes treated as one potential alarm bell rather than as an outcome (Khalatur et al. 2022; Sinković, Zemla, and Zemla 2022). Siranova and Radvanský (2018) retrospectively evaluate the MIP indicators as early-warning tools for 17 Central and Eastern European economies covering 1991–2014, defining crises as years in which real GDP growth falls more than one standard deviation below its five-year average and testing one-year-ahead signals within a two-year prediction window. Using a signalling framework with AUROC, absolute-utility (loss-function) metrics and noise-to-signal diagnostics, they show that labour-market "internal imbalance" indicators – closely aligned with today's social MIP items such as unemployment, youth and long-term unemployment, participation/activity, employment and NEET (neither in employment nor in education and training) – typically perform poorly at the Commission's official thresholds, often yielding AUROC values below 0.5 and negative absolute utility (i.e., no gain over a random benchmark). Optimising thresholds improves performance only modestly for most labour-market measures. However, the youth NEET rate emerges as a notable exception when calibrated around a 25% threshold, delivering positive utility and comparatively strong noise-to-signal properties. Overall, their evidence suggests that social/labour indicators generate substantial short-run "noise" as crisis predictors and are better interpreted as slow-moving structural imbalance measures to be assessed in-depth – an interpretation that motivates our broader test of whether social MIP indicators add independent information beyond non-social macro-financial indicators, or are largely redundant once the latter are accounted for.

Likewise, Boysen-Hogrefe et al. (2015) and Erhart, Becker, and Saisana (2018) point to a constrained role of the social (labour-market) dimension within the MIP when the framework is assessed through an early-warning lens. In a signalling-based evaluation of the scoreboard, unemployment – the key social item in earlier vintages – exhibits weak crisis-discrimination and low "usefulness" even after threshold optimisation, implying little actionable warning content for financial crises. Consistent with this evidence, broader assessments emphasise that the labour-market indicators later incorporated into the scoreboard (e.g., participation/activity, long-term unemployment, NEET) are mainly designed to inform the economic reading in in-depth reviews rather than to serve as hard procedural triggers, and that the scoreboard's overall performance as an EWS remains at best modest.

There is virtually no research explicitly examining whether the social imbalance indicators are systematically associated with other macroeconomic developments. This is an important gap, given that social outcomes might not move in lockstep with macroeconomic aggregates. For example, Europe's official poverty metrics are relative the at-risk-of-poverty rate measures the share of people below 60% of the median income. Strong GDP growth might not reduce this rate if income gains are unevenly distributed. Indeed, persistent inequality can mean that relative poverty and social exclusion remain high even during economic expansions.

The social MIP indicators, compared to measures used by organisations like the World Bank (2025), OECD (2025) and developed jointly by the Oxford Poverty and Human Development Initiative (OPHI) and the United Nations Development Programme (UNDP) (Oxford Poverty and Human Development Initiative 2025) are more focused on the causes of poverty, particularly unemployment in various dimensions. Additionally, there are measures of poverty or social exclusion, including after accounting for social transfers, expressed as the share of such individuals in the total population. While the World Bank's Multidimensional Poverty Index is better suited to significantly poorer countries than those in the European Union, both OECD Social Indicators and MIP social indicators assess social conditions but serve different purposes. The OECD indicators provide a broad assessment of well-being and inequality across developed economies. In contrast, MIP social indicators are part of the EU's economic surveillance mechanism, focusing on social imbalances that may affect macroeconomic stability.

In summary, prior studies provide mixed evidence on which economic indicators are most important for anticipating crises, but they collectively highlight that macro-financial indicators (external balances, credit and asset prices) are critical. However, the "social imbalances" – issues like unemployment and poverty – have not been systematically studied in terms of their relationship with those macroeconomic indicators. Our analysis hence attempts to bridge this gap by investigating to what extent changes in social indicators can be statistically linked to the behaviour of macroeconomic imbalance indicators in the EU.

Data and Methodology

To empirically evaluate the prospective predictive power of macroeconomic imbalances on social outcomes, we employ a multi-methodological approach combining penalised regression, stepwise econometric selection, and non-parametric machine learning. This triangulation of methods allows us to mitigate the specific limitations of individual models, such as multicollinearity in standard regression or the lack of interpretability in "black box" algorithms. The analysis utilises a balanced panel of 27 EU Member States over the period 2001–2023 ($N = 27$, $T = 23$), comprising 621 country-year observations.

The panel's temporal dimension spans multiple economic cycles, including the global financial crisis, the European sovereign debt crisis, and the COVID-19 pandemic, thus providing substantial variation necessary for robust econometric identification. The dataset was constructed by integrating information from multiple authoritative sources, primarily Eurostat's Macroeconomic Imbalance Procedure database, supplemented with data from the European Commission's AMECO database and the European Central Bank's Statistical Data Warehouse, where necessary for completeness and cross-validation.

We focus on ten social indicators (dependent variables) and twenty-six non-social indicators (explanatory variables). The social indicators include the two headline (main) social MIP indicators as well as eight auxiliary social indicators without pre-set thresholds (Appendix 1). Together, these variables capture the major employment and social inclusion dimensions of the EU's social objectives (Appendix 2).

Variable Selection via LASSO

Given the high dimensionality of the potential regressor set relative to the time series length for individual countries, we first employ the Least Absolute Shrinkage and Selection Operator (LASSO) to identify the most relevant predictors. Following the seminal framework established by Tibshirani (1996), LASSO performs variable selection and regularisation to enhance the prediction accuracy and interpretability of the statistical model (Bickel, Ritov, and Tsybakov 2009; Carrico et al. 2015; Alshqaq and Abuzaid 2023).

The LASSO estimator minimises the residual sum of squares subject to the sum of the absolute value of the coefficients being less than a constant. Formally, for each social indicator y, we solve the following optimisation problem:

$$\widehat{\beta}_{\text{LASSO}} = \arg\min_{\beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(y_{\text{it}} - x_{\text{it}}^{'} \beta \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\},$$

where x_{it} is the vector of macroeconomic predictors, β is the vector of coefficients, and $\lambda >= 0$ is the tuning parameter controlling the strength of the penalty. When λ is sufficiently large, some coefficients are forced to be exactly zero, effectively selecting a sparse subset of predictors. Prior to estimation, all variables are standardised to ensure the penalty is applied uniformly across regressors with different scales.

We run separate LASSO regressions for each of the ten social indicators, using the full set of 26 non-social indicators as candidate predictors. The regressions are panel-based in the sense that we include country and year fixed effects (via demeaning and year dummies) so that the LASSO picks up within-country, over-time associations. All variables are standardised to zero mean and unit variance prior to estimation to allow direct comparison of coefficient magnitudes. We select the LASSO tuning parameter through ten-fold cross-validation, minimising the mean squared error following Carrico et al. (2015) and Ghatari, Aminghafari, and Mohammadpour (2024). This yields a sparse model for each social indicator, including only the subset of non-social predictors with non-zero coefficients. We interpret a non-zero LASSO coefficient as evidence that the corresponding macro variable helps explain variation in the social indicator (after controlling for other variables). The sign and relative size of the coefficient β indicate the direction and strength of the association. Following a heuristic common in applied LASSO studies (Tibshirani 1996; Schmidt and Makalic 2017), we treat any standardised coefficient larger than 0.25 in absolute value as a strong association.

Two-Stage Panel Data Approach

As a complementary method to LASSO, we implement a two-stage selection procedure designed to handle panel data heterogeneity explicitly.

Stage 1: Univariate Pre-screening. In the first stage, we conduct a univariate screening process to filter out irrelevant predictors. For each social indicator, we estimate bivariate panel regressions with fixed effects against each of the 26 macroeconomic variables. Variables that fail to meet a liberal significance threshold (p-value < 0.20) are discarded to reduce noise before the multivariate analysis.

Stage 2: Fixed-Effects Estimation. In the second stage, the surviving regressors are included in a multivariate Fixed Effects (FE) model. The specification is given by:

$$Y_{\text{it}} = \beta X_{\text{it}} + \mu_i + \varepsilon_{\text{it}},$$

where μ_i denotes the time-invariant country-specific effects, and ε_{it} is the idiosyncratic error term. Crucially, we employ the within-transformation (demeaning) to eliminate μ_i. Consequently, no global intercept (α) appears in the final equation, as it is absorbed by the fixed effects (or equals zero after centring the data). This approach ensures that our estimates are driven by within-country variations over time, consistent with the logic of the MIP surveillance, which monitors the evolution of imbalances. Inference is based on cluster-robust standard errors (HC1) to account for serial correlation and heteroscedasticity within panels (Cameron and Miller 2015).

This two-stage procedure ensures that we capture cases where a macro variable may be a good individual predictor but could be dominated by others when in the same model (Masakure 2015; Feng, Tong, and Chiu 2023). The outcome of this method is a set of conventional regression coefficients and *p*-values linking social and macro variables, which we can compare with the LASSO results.

Random Forest Analysis

To check the robustness of our linear specifications and capture potential non-linearities, we employ the Random Forest algorithm (Breiman 2001). Unlike linear regression, Random Forest builds an ensemble of decorrelated decision trees, providing a measure of variable importance without assuming a specific functional form (Strobl et al. 2007; Schauberger, Klug, and Berger 2024). For each social indicator, we grow a random forest using 500 regression trees, using all non-social indicators as inputs (with fixed country and time effects incorporated as additional features).

We report two key metrics of variable importance:

1. **%IncMSE (Increase in Mean Squared Error):** Measures the decrease in model accuracy when the values of a variable are randomly permuted. A higher value indicates that the variable is critical for prediction.

2. **IncNodePurity (Increase in Node Purity):** Measures the total decrease in node impurity (residual sum of squares) that results from splits over a variable, averaged over all trees.

To facilitate interpretation, we classify the variable importance into qualitative categories (Low, Moderate, High, Very High) based on the quartile distribution of these metrics across all predictors. This relative ranking avoids arbitrary thresholds and reflects the comparative predictive power of each macroeconomic variable.

This non-parametric approach serves as a validation tool: if the Random Forest identifies the same key predictors as LASSO and the FE model, our findings regarding the macroeconomic predictors of social imbalances are robust to model specification.

After applying all three methods, we compile the results to identify a set of robust associations between social indicators and macroeconomic variables. We consider a relationship robust if it appears in at least two of the approaches. The combination of approaches helps mitigate the limitations of any single method and provides a triangulation of evidence.

We must acknowledge the limitations of our approach regarding causal inference. First, while our models are specified with social indicators as dependent variables, this does not preclude the existence of reverse causality. For example, while a high level of non-performing loans (GNPL) might be a predictor for a rise in the unemployment rate (UR), it is also highly likely that high unemployment contributes to an increase in non-performing loans. Second, although the models control for time-invariant country-specific characteristics (fixed effects) and common shocks (time effects), the risk of omitted variable bias remains. Third, establishing definitive causal links would require different research strategies, such as instrumental variable (IV) models or dynamic panel models (e.g., GMM), which are beyond the scope of this predictive analysis but represent a promising avenue for future research.

We do not apply formal panel unit-root tests, as our primary objective is predictive assessment rather than cointegration analysis; the country and year fixed effects absorb time-invariant country heterogeneity and common shocks, while the out-of-sample validation framework provides a direct test of whether estimated relationships generalise beyond the estimation sample.

Results

The results of the **LASSO estimation** are presented in a matrix format: rows correspond to the 26 non-social macroeconomic variables (regressors), columns to the ten social variables (dependent variables), and cells contain the estimated LASSO coefficient for a given regressor in a given model.

To evaluate the results, a heuristic scale was applied to interpret the strength of LASSO coefficients, assuming that a strong association is present when the absolute value of beta exceeds 0.25. This threshold takes into account the typical distribution of LASSO coefficients, which are often small and rarely exceed 0.5 – unless the effect is genuinely substantial. In the analysed sample, 12 such cases were observed. Table 1 presents the results.

Table 1. Lasso demeaned results

Social MIP	Regressor	Beta
UR	NULC3	− 0.27
UR	EMS3	0.26
UR	GNPL	0.33
LTUR	NULC3	− 0.26
LTUR	GNPL	0.37
YUR	NULC3	− 0.25
ER	GNPL	− 0.33
YPEE	NULC3	− 0.27
YPEE	RGDP	− 0.39
PRPEST	NFCD	0.29
SMDP	HHCF1	− 0.28
PLH	RGDP	− 0.31

Source: own calculations.

In Table 2, we summarise the final multivariate fixed-effects estimates obtained from the two-stage procedure described above. For comparability across outcomes and predictors, the reported coefficients are fully standardised: within each final (equation-specific) estimation sample after listwise deletion of missing observations the dependent variable and all retained regressors are transformed into z-scores (mean zero, unit variance) prior to estimation. Hence, each $\widehat{\beta}_k$ can be interpreted as the change in a social MIP (in standard deviations) associated with a one-standard-deviation increase in the corresponding non-social MIP, conditional on the other retained predictors and the country and year fixed effects. Statistical inference relies on country-clustered, HC1 cluster-robust standard errors.

To facilitate interpretation of practical relevance, we label the magnitude of each effect using the absolute value of the coefficient $\widehat{\beta}_k$: very weak (< 0.05), weak (0.05–0.20), moderate (0.20–0.50), strong (0.50–1.00), and very strong (≥ 1.00). The cut-offs at 0.20 and 0.50 are used as heuristic reference points consistent with widely cited "small/medium/large" conventions for unit-free effect sizes in the behavioural and social sciences (Cohen 1988:25–27 for d; 79–80 for r), while recognising Cohen's explicit caution that such conventions are context-dependent and should be treated only as a frame of reference when no better substantive calibration is available. Accordingly, these magnitude labels complement rather than replace formal inference. In Table 2, we highlight coefficients that are both non-trivial in magnitude ($|\widehat{\beta}_k| > 0.20$) and statistically distinguishable from zero at a chosen level (p < 0.10), enabling a concise comparison of non-social MIPs that appear most relevant for explaining standardised social outcomes.

Table 2. Final results from the two-stage pre-screening and multi-variate fixed effects

Social MIP	Regressor	Coefficient	Strength	*p*-value
UR	NULC3	− 0.21	moderate	0.002 292
UR	GDERD	− 0.27	moderate	0.047 313
UR	GNPL	0.27	moderate	0.000 004
LTUR	NIIPE	− 0.29	moderate	0.061 414
LTUR	GNPL	0.26	moderate	0.000 062
YUR	NULC3	− 0.21	moderate	0.00 772
YUR	GGSD	− 0.60	strong	0.059 145
YUR	GDERD	− 0.29	moderate	0.047 125
ER	HHDGDP	− 0.36	moderate	0.098 224
ER	HHDGDI	0.51	strong	0.049 037
YPEE	NIIPE	− 0.25	moderate	0.026 093
PRPE	HHDGDP	0.48	moderate	0.034 711
PRPE	HHDGDI	− 0.56	strong	0.016 039
PRPEST	NIIPE	− 0.32	moderate	0.00 712
PRPEST	RGDP	− 0.43	moderate	0.072 673
PLH	HHDGDP	0.73	strong	0.040 653
PLH	RGDP	− 0.93	strong	0.054 583
PLH	HHDGDI	− 0.69	strong	0.008 639

Source: own calculations.

For eight social MIPs, at least one non-social variable was found to be significantly associated with changes in the corresponding social outcome. In our analysis, the fully standardised coefficients allow for a direct comparison of effect sizes across different non-social MIPs. For example, for the unemployment rate (UR), the non-social variable gross non-performing loans of domestic and foreign entities as a percentage of gross loans (GNPL) exhibits a moderate association, with a standardised coefficient of 0.27. This implies that, holding other factors constant, a one-standard-deviation increase in GNPL is associated with a 0.27 standard deviation increase in UR.

Overall, these findings indicate that a small subset of macro-financial indicators displays non-trivial predictive associations with several social indicators within our standardised panel framework. This full standardisation improves comparability and highlights the practical relevance of the selected predictors, providing insight into informational linkages between non-social and social MIP indicators.

The **random forest results** produced a table containing all social MIP variables, all regressors (the explanatory variables whose importance was assessed, including both non-social indicators and the factors "country" and "year"), and two measures: *IncMSE* and *IncNodePurity*. In both cases, higher values signify a stronger predictive contribution of the regressor and thus reflect greater overall importance of that regressor.

There are no universal, fixed thresholds for *IncMSE* or *IncNodePurity*, because their absolute values depend on the underlying data and the specific model. In practice, these values are compared relative to each other within the same model. A common approach is to examine the distribution of importance values across predictors and then define custom thresholds. We classified the variables as follows:

- very high importance: predictors with values above the 75th percentile,
- high importance: predictors between the 50th and 75th percentiles,
- medium importance: predictors between the 25th and 50th percentiles,
- low importance: predictors below the 25th percentile.

Although these cut-offs are arbitrary, they enable a meaningful relative ranking of the predictors. Table 3 includes only those rows where *IncMSE* values were classified as "very high importance" and *IncNodePurity* values as either "high" or "very high importance". This selection reflects the fact that while *IncNodePurity* provides an additional perspective, primary emphasis should be placed on *IncMSE* when ranking predictors, as it offers a more robust measure of variable importance in the presence of correlated inputs.

Table 3. Random forest variable importance for social MIP indicators

Social MIP	Regressor	*IncMSE*	*IncMSE* cat.	*IncNodePurity*	*IncNodePurity* cat.
UR	NULC3	10.99	Very high	159.66	High
UR	GGSD	10.88	Very high	283.24	Very high
UR	HHCF1	10.68	Very high	344.01	Very high
UR	HPIN	13.03	Very high	134.75	High

Social MIP	Regressor	*IncMSE*	*IncMSE* cat.	*IncNodePurity*	*IncNodePurity* cat.
UR	NIIPE	10.50	Very high	114.03	High
UR	GNPL	10.69	Very high	194.60	Very high
UR	BP	15.44	Very high	519.23	Very high
LTUR	NIIP	13.08	Very high	123.31	High
LTUR	GNPL	14.22	Very high	159.37	High
LTUR	BP	18.21	Very high	380.64	Very high
YUR	NIIP	10.72	Very high	770.67	Very high
YUR	GGSD	14.13	Very high	2336.42	Very high
YUR	HHCF1	11.34	Very high	1190.25	Very high
YUR	HPIN	10.91	Very high	581.47	Very high
YUR	NIIPE	12.72	Very high	808.84	Very high
YUR	RGDP	11.39	Very high	348.21	Very high
YUR	BP	16.34	Very high	2918.54	Very high
ER	NULC3	11.28	Very high	173.12	High
ER	GGSD	14.06	Very high	620.31	Very high
ER	HHDGDP	10.56	Very high	137.71	High
ER	HPIN	10.86	Very high	228.10	Very high
ER	NIIPE	11.11	Very high	130.43	High
ER	RGDP	11.50	Very high	281.20	Very high
ER	GDERD	10.33	Very high	271.83	Very high
ER	GNPL	20.34	Very high	1209.07	Very high
ER	BP	15.43	Very high	1032.14	Very high
YPEE	CAB3	13.06	Very high	239.87	Very high
YPEE	NIIP	14.22	Very high	346.92	Very high
YPEE	HPIN	11.71	Very high	180.46	High
YPEE	RGDP	13.42	Very high	305.26	Very high
YPEE	HHDGDI	11.80	Very high	100.36	High
YPEE	GNPL	10.74	Very high	492.87	Very high
YPEE	BP	13.70	Very high	443.35	Very high
PRPE	HHDGDP	11.18	Very high	756.16	Very high

Social MIP	Regressor	*IncMSE*	*IncMSE* cat.	*IncNodePurity*	*IncNodePurity* cat.
PRPE	NFCD	11.88	Very high	153.98	High
PRPE	HHCF1	10.49	Very high	197.96	Very high
PRPE	RGDP	16.08	Very high	1490.70	Very high
PRPE	GDERD	13.50	Very high	682.84	Very high
PRPE	BP	15.78	Very high	450.91	Very high
PRPEST	GGSD	13.89	Very high	158.99	High
PRPEST	HHDGDP	10.73	Very high	118.30	High
PRPEST	RGDP	10.71	Very high	194.75	Very high
PRPEST	GDERD	15.96	Very high	411.45	Very high
PRPEST	BP	12.39	Very high	118.29	High
SMDP	HHDGDP	11.47	Very high	1080.58	Very high
SMDP	RGDP	15.82	Very high	2390.70	Very high
SMDP	GNPL	10.50	Very high	496.18	Very high
PLH	NULC3	16.60	Very high	278.06	Very high
PLH	NFCD	12.49	Very high	108.95	High
PLH	HHCF1	12.43	Very high	164.32	High
PLH	BP	10.35	Very high	74.15	High

Source: own calculations.

Although all three methods applied can be classified under the umbrella of multiple regression analysis and variable selection, they nonetheless represent distinct approaches to identifying which social MIP variables may be considered "redundant" in the sense that they exhibit significant associations with non-social MIP indicators. The results from the analyses reveal that most social MIP indicators have at least one significant association with a macroeconomic variable. Table 4 presents the results indicating which social MIP variables are linked to non-social MIP variables, based on the application of three methods: LASSO, stepwise regression procedure, and random forest. For a given non-social MIP variable to be included in the table, it had to be identified by at least two of the three methods.

Eight of the ten social indicators examined exhibit a clear relationship with one or more non-social MIP indicators. For the labour force participation rate (LFPR3), none of the methods identified such a relationship. In the case of the rate of severely materially deprived people (SMDP), potential associations with specific non-social variables were indicated by only one of the methods in a few instances.

Table 4. A summary of the findings on the relationships between social and non-social dimensions of the MIP

Method	Multiple Regression Analysis and Variable Selection		
	LASSO	Two-stage selection	Forest
Social MIP	Non-social MIP		
UR	GNPL (+)	GNPL (+)	GNPL
UR	NULC3 (–)	NULC3 (–)	NULC3
LFPR3			
LTUR	GNPL (+)	GNPL (+)	GNPL
YUR	NULC3 (–)	NULC3 (–)	
YUR		GGSD (–)	GGSD
ER	GNPL (–)		GNPL
ER		HHDGDP (–)	HHDGDP
YPEE	RGDP (–)		RGDP
PRPE		HHDGDP (+)	HHDGDP
PRPEST		RGDP (–)	RGDP
SMDP			
PLH	RGDP (–)	RGDP (–)	

Source: own calculations.

Notably, the **unemployment rate (UR)** is strongly linked to two macroeconomic indicators: higher nominal unit labour cost growth (NULC3) is associated with a lower UR (suggesting that wage growth tends to coincide with falling unemployment in an economic upswing), whereas higher non-performing loan levels (GNPL) are associated with a higher UR (consistent with financial stress leading to job losses). These relationships were the most consistently identified linkage across methods (flagged by LASSO, two-stage selection, and random forest alike).

Similarly, for the **long-term unemployment rate (LTUR)**, the share of gross non-performing loans (GNPL) in the banking sector proves to be a significant positive predictor: an increase in the proportion of non-performing loans is associated with a rise in long-term unemployment. This observation is consistent with theoretical expectations, as banking sector distress typically coincides with economic downturns that extend the duration of unemployment spells. The causality may also operate in the opposite direction: elevated unemployment can undermine debt servicing capacity, particularly among first-time borrowers with limited income stability.

Conversely, a higher gross non-performing loans ratio (GNPL) is associated with a lower **employment rate (ER)** defined as the share of working-age adults in employment reinforcing the notion that financial crises and weak credit conditions are closely linked to labour market fragility. This relationship is supported by the results of both the LASSO and random forest methods.

A similar, and as in the previous case less robust pattern is found for **youth unemployment (YUR)**, which, like overall unemployment, correlates negatively with unit labour cost growth (NULC3) and general government gross debt as a percentage of GDP (GGSD), the latter relationship being supported by the random forest method.

Turning to poverty and social exclusion indicators, we find that overall economic growth plays a key role in improving several outcomes. In particular, a rise in real GDP per capita in EUR (RGDP) is strongly associated with subsequent reductions in the **share of youth not in employment, education or training (YPEE)**, the **people at risk of poverty after social transfers (PRPEST)**, and the **very low work intensity rate (PLH)** all three of these social indicators decline when real incomes grow. Quantitatively, RGDP per capita was among the top predictors for those variables in the LASSO and two-stage selection models, indicating that a stronger economy leads to fewer young people disengaged from work or education and fewer households in (relative) poverty or joblessness. However, it is noteworthy that the indicator **people at risk of poverty or social exclusion (PRPE)** a broader composite measure did not exhibit a significant association with real GDP growth, but rather with household debt, including non-profit institutions serving households, consolidated; % of GDP). This suggests that general economic growth alone may not reduce relative poverty or social exclusion rates, possibly because the gains from growth are not evenly distributed.

Two social indicators stand out as not well-explained by the macro variables. The **labour force participation rate, as a percentage of the population aged 15–64 (LFPR3)**, measured as a three-year change, had no predictors among the 26 macro indicators. This implies that fluctuations in participation (the proportion of people active in the labour market) are associated with factors other than the monitored macroeconomic imbalances for example, demographic changes, education enrolment, migration, or policy reforms affecting retirement and childcare, which are not captured by the MIP scoreboard. Similarly, the **severely materially deprived people (SMDP; % of total population)** showed no consistent links to macroeconomic indicators. This indicator, which reflects extreme hardship, may be more influenced by social safety nets, targeted aid, and other social policies that mitigate deprivation independently of the economic cycle.

Out-of-Sample Prediction Results

To rigorously assess whether macroeconomic variables genuinely contain predictive information about social indicators rather than merely fitting in-sample noise we complement our estimation with out-of-sample prediction tests (Hastie, Tibshirani, and Friedman 2009). While in-sample metrics establish statistical associations, out-of-sample validation tests whether these patterns generalise across different national contexts.

We implement **Leave-One-Country-Out Cross-Validation (LOCO-CV)**, a variant of cross-validation specifically designed for panel data with grouped observations (Arlot and Celisse 2010). The procedure iterates through all $N = 27$ Member States; in each iteration, we:

1. Exclude all observations belonging to country *i* (the test set).
2. Train the models (LASSO and random forest) on the remaining *N* – 1 countries (the training set).
3. Predict the social indicator values for the held-out country *i*.

This approach ensures that the model never "sees" data from the target country during training, mimicking a true forecasting scenario where policy decisions must be made for a specific member state based on general EU-wide regularities.

We report the out-of-sample coefficient of determination R^2_{oos} as the primary performance metric:

$$R^2_{\text{OOS}} = 1 - \frac{\sum \left(y_{\text{it}} - \hat{y}_{\text{it}}\right)^2}{\sum \left(y_{\text{it}} - \overline{y}_{\text{train}}\right)^2},$$

where y_{it} denotes the observed value of the social indicator for country *i* at time *t*, $\hat{y}_{it}$ is the model's prediction, and $\bar{y}_{train}$ represents the mean of the observed values in the test set.

Table 5 presents the out-of-sample predictive performance, offering a rigorous test of whether macro-financial variables contain predictive information for social outcomes across different national contexts. The results reveal a striking dichotomy between indicators that are well-predicted by the macro-financial block and those that show weak or no links to it.

Table 5. Out-of-sample predictive performance

Social MIP	LASSO R2	RF R2	LASSO RMSE
UR	0.346	0.430	3.41
LTUR	0.439	0.576	2.19
YUR	0.329	0.447	7.91
ER	−0.453	0.438	7.43
LFPR3	−0.140	0.122	1.45
SMDP	0.297	0.697	5.85
PRPE	0.264	0.489	5.52
PRPEST	−0.655	0.045	4.93
YPEE	0.494	0.307	3.43
PLH	0.133	0.149	2.96

Source: own calculations.

First, labour market exclusion is moderately predictable, but often requires non-linear modelling. The Random Forest model achieves substantial predictive power for Long-term Unemployment (R^2 = 0.58) and Youth Unemployment (R^2 = 0.45). Interestingly, for the Employment Rate (ER), the linear LASSO model fails completely (R^2 = –0.45), while the non-linear random forest recovers predictive power (R^2 = 0.44). This suggests that while employment is linked to macro-fundamentals, the relationship is complex and may not be captured by simple threshold-based monitoring.

Second, and most critically for the policy debate, we observe a fundamental decoupling of poverty outcomes. While Severe Material Deprivation (SMDP) which is closely tied to GDP levels is highly predictable (R^2 = 0.70 in RF), the At-risk-of-poverty rate after social transfers (PRPEST) is virtually unpredictable from macroeconomic variables. The Random Forest R^2 for PRPEST is near zero (0.045), and LASSO performs worse than a random guess (–0.655).

This result indicates that macroeconomic conditions are associated with pre-transfer deprivation, whereas post-transfer poverty outcomes show limited predictive links with the macro-financial variables monitored by the MIP scoreboard in our modelling framework. This pattern suggests that post-transfer poverty may be influenced by country-specific tax-and-benefit institutions that are not proxied by the MIP's macro-financial indicators.

Discussion and Conclusion

This study examined the incremental diagnostic content of social indicators within the EU's Macroeconomic Imbalance Procedure scoreboard. Three principal findings emerge from our LASSO, two-stage selection, and random forest analyses. First, social indicators, particularly unemployment and poverty measures, tend to co-move with the non-social macro-financial scoreboard. Our models suggest that variables such as gross non-performing loans, nominal unit labour costs, real GDP per capita, and household debt are associated with a notable share of variation in employment and deprivation metrics, though the strength of these relationships varies across specifications. Second, we find marked heterogeneity across social indicators. While eight of the ten social outcomes exhibit robust associations with at least one macro-financial variable, the labour force participation rate shows no such linkages, and severe material deprivation displays distinct non-linear dynamics linked predominantly to income levels. This heterogeneity suggests that not all social outcomes respond uniformly to macro-financial developments. Third, our out-of-sample predictive exercises reveal that macro-financial variables explain a substantial share of variation in most labour market indicators, with random forest models achieving R^2 values between 0.43 and 0.58 for unemployment measures. However, predictive performance varies markedly: while severe material deprivation is highly predictable from macroeconomic conditions (RF R^2 = 0.7), the at-risk-of-poverty rate after social transfers remains virtually unpredictable (RF R^2 = 0.05). This pattern suggests that post-transfer poverty is only weakly linked to the macro-financial information set captured by the MIP scoreboard and may be influenced by country-specific tax-and-benefit institutions not proxied by these variables.

Our results suggest that most social indicators co-move with the macro-financial information set captured by the non-social scoreboard, with limited incremental predictive information beyond this non-social block in our modelling framework. The unemployment rate, for instance, is linked to gross non-performing loans and nominal unit labour cost growth, relationships consistently identified across all three methods. When unemployment or poverty thresholds are breached, this typically occurs after more fundamental economic imbalances have accumulated. This temporal hierarchy aligns with established research on business cycle dynamics. Cerra, Fatás, and Saxena

(2023) demonstrate that negative output shocks generate persistent labour market hysteresis, with unemployment recovering significantly slower than GDP. Bluedorn and Leigh (2019) corroborate this asymmetry, finding that labour force participation often fails to revert to pre-crisis levels for years following economic shocks. Similarly, the World Bank (2022) documents that poverty rates spike rapidly during downturns but decline sluggishly during expansions. Our results provide EU-specific evidence consistent with these broader patterns.

The findings also resonate with earlier evaluations of MIP scoreboard performance. Siranova and Radvanský (2018) show that labour-market indicators typically perform poorly as crisis predictors at official thresholds, often yielding AUROC values below 0.5. Boysen-Hogrefe et al. (2015) similarly find that unemployment exhibits weak crisis-discrimination even after threshold optimisation. Our results extend these insights by demonstrating that the informational content of social indicators is largely absorbed by macro-financial variables once both are considered jointly. However, our analysis reveals important nuances absent from earlier studies. The striking contrast between highly predictable severe material deprivation and virtually unpredictable post-transfer poverty rates suggests that while macroeconomic conditions are associated with the potential for deprivation through market income, final poverty outcomes show only weak links to the macro-financial variables monitored by the MIP scoreboard, consistent with the interpretation that country-specific tax-and-benefit institutions play a mediating role. Similarly, the complete absence of macro-financial predictors for the labour force participation rate suggests that this indicator may be linked to demographic shifts, education enrolment, migration, and policy reforms affecting retirement and childcare rather than to cyclical imbalances.

Our results can be situated within the broader literature on MIP indicator performance. Dany-Knedlik, Kämpfe, and Knedlik (2021), evaluating the MIP scoreboard for Central and Eastern European economies, find no statistically meaningful thresholds for labour-market indicators and recommend their exclusion from crisis-discrimination exercises. Our results are consistent with this finding: once macro-financial variables are accounted for, social indicators contribute limited additional predictive content in our out-of-sample framework. Regarding specific indicators, our results both confirm and qualify prior findings. Knedlik (2014) reports positive utility for unemployment at the original MIP thresholds, and in our framework, unemployment is predicted by the macro-financial block, particularly non-performing loans and unit labour costs. This pattern suggests substantial overlap in informational content between unemployment and selected macro-financial indicators, rather than indicating independent incremental predictive information.

Domonkos et al. (2017) identify the participation rate as one of the most relevant MIP indicators based on factor analysis. Our predictive framework offers a complementary perspective: the labour force participation rate shows no robust association with the non-social block across methods. This difference is consistent with the distinct objectives of the approaches: factor analysis summarises common co-movement across indicators, whereas we evaluate out-of-sample predictive relationships from the non-social block to social indicators.

Finally, while Bacchini, Ruggeri Cannata, and Donà (2020) conclude that social MIP indicators are useful for investigating well-being across Member States, our results are fully consistent with this interpretation. We do not argue that social indicators lack value; rather, our results suggest that they remain important for welfare monitoring and for interpreting the social dimension of imbalances, while their incremental predictive information beyond the macro-financial (non-social) block appears limited within our framework.

Our results hold several **implications for European economic governance and social policy coordination**. Regarding MIP architecture, we recommend treating social indicators as complementary diagnostics rather than primary procedural triggers within the preventive arm. The MIP could continue reporting social outcomes to provide a holistic assessment, which remains politically essential given the need to highlight social distress, as demonstrated in post-crisis in-depth reviews. However, decisions to trigger warnings or corrective action should depend primarily on macro-financial indicators, with social metrics serving to contextualise severity and tailor policy responses. For instance, when macro indicators signal an imbalance alert, the severity of associated social indicators could guide whether recommended measures should include strengthened social protection measures or employment programmes.

Our findings also support establishing a **dedicated Social Convergence Framework** alongside the MIP. The near-zero predictability of post-transfer poverty from macroeconomic variables is consistent with the rationale for separate surveillance of social policies. Certain auxiliary social outcomes – such as severe material deprivation and very low work intensity (a proxy for labour market exclusion) – may be less amenable to uniform, threshold-based macro surveillance. These indicators are currently included in the MIP scoreboard as auxiliary items without formal thresholds (Appendix 1) and are therefore best interpreted as complementary diagnostics rather than threshold-based procedural triggers. A separate mechanism could monitor and address these challenges with appropriate tools, including targeted reforms, investment in social inclusion, and deployment of EU social funds. Such separation would allow the EU to pursue social objectives without diluting the MIP's core mandate of preventing macroeconomic crises.

At the national level, we document robust within-country associations between non-performing loans and unemployment, and between real GDP growth and lower youth disengagement and low work intensity indicating systematic co-movement between macro-financial indicators and selected social outcomes in the EU data. However, the link between macroeconomic conditions and social welfare is not uniform across all dimensions. The unpredictability of post-transfer poverty from macro variables indicates that factors such as the design of tax-and-benefit systems, income inequality, and regional disparities may weaken the association between aggregate growth and poverty outcomes (Knedlik 2014). Active labour market policies, education, and training are widely considered essential for broadly shared prosperity (Card et al. 2018), while strong automatic stabilisers are associated with smaller social costs of temporary shocks (Dolls, Fuest, and Peichl 2012).

Several **limitations** of this study warrant acknowledgement. Our analysis relies on annual scoreboard data, which may obscure higher-frequency dynamics relevant for early-warning purposes. Monthly or quarterly indicators, where available, could provide more granular insights into lead-lag relationships between macro-financial and social variables. Additionally, our panel approach treats EU member states as relatively homogeneous units within estimation. While we control for country fixed effects, remaining cross-country heterogeneity in labour market institutions, social protection systems, and economic structures may affect the stability and cross-country generalisability of the estimated associations. Future research could employ regime-switching models or cluster-specific estimations to capture this heterogeneity more fully. We also focus on the existing MIP indicator set, whereas alternative social metrics, including measures of income inequality, housing affordability, or health outcomes, may exhibit different relationships with macro-financial conditions. Finally, our analysis cannot fully disentangle causation from correlation. While the patterns we observe are consistent with macro-financial conditions driving social outcomes, reverse causality is plausible for some relationships, as we note for non-performing loans and unemployment, and omitted variable bias cannot be definitively excluded.

In conclusion, this study demonstrates that the MIP's social indicators possess limited incremental utility as advance-warning signals once the non-social scoreboard is observed, while remaining vital as measures of societal well-being and as inputs into the broader assessment of imbalances. The key empirical contribution is to document pronounced heterogeneity in out-of-sample predictive performance: labour-market indicators and severe material deprivation achieve moderate-to-high R^2 in LOCO-CV when predicted from the non-social scoreboard, whereas post-transfer poverty exhibits near-zero out-of-sample predictability in our models. From a governance perspective, these results support monitoring both macro-financial conditions and social outcomes: macro-financial indicators contain predictive information relevant for several labour-market variables, whereas some poverty measures show only weak links to the non-social scoreboard and may require complementary analytical frameworks focused on social-policy and institutional factors. European economic governance could be strengthened by streamlining the MIP to focus on core macroeconomic risks while simultaneously developing parallel mechanisms, potentially a formalised Social Convergence Framework, to monitor and address social outcomes with appropriate expertise and political visibility. Such rebalancing would advance the ultimate aim of EU governance: not merely avoiding crises, but promoting a high-employment, socially inclusive Union without conflating causes and effects.

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Appendix 1. MIP scoreboard indicators*: main (1–13) and *auxiliary* (14–36)

No.	Variable	Description	Thresholds
1	CAB3	Current account balance – % of GDP, 3–year average	–4%/6%
2	NIIP	Net international investment position – % of GDP	–35%
3	REER3	Real effective exchange rate, 42 trading partners – 3-year % change	±3% (EA) / ±10% (non-EA)
4	EXP3	Export performance against advanced economies – 3-year % change	–3%
5	NULC3	Nominal unit labour cost index (per hour worked) – 3-year % change	9% (EA) / 12% (non-EA)
6	GGSD	General government gross debt – % of GDP	60%
7	HHDGDP	Household debt including non-profit institutions serving households, consolidated – % of GDP	55%
8	NFCD	Non-financial corporations' debt, consolidated – % of GDP	85%
9	HHCF1	Household credit flow including non–profit institutions serving households, consolidated – % debt stock (*t* – 1)	14%
10	NFCCF1	Non-financial corporations' credit flow excluding foreign direct investment, consolidated– % debt stock (*t* – 1), excluding foreign direct investment	13%
11	HPIN	House price index, nominal – 1 year % change	9%
12	**UR**	**Unemployment rate – % of labour force aged 15–74**	**10%**
13	**LFPR3**	**Labour force participation rate – 3–year change in pps (% of population aged 15–64)**	**–0.2%**
14	*NIIPE*	*Net international investment position excluding non-defaultable instruments – % of GDP*	
15	*NLB*	*Net lending / borrowing (current account + capital account) – % of GDP*	
16	*NTBEP*	*Net trade balance of energy products – % of GDP*	
17	*RGDP*	*Real GDP per capita – EUR*	
18	*GFCF*	*Gross fixed capital formation – % of GDP*	
19	*GDERD*	*Gross domestic expenditure on R&D in % of GDP*	
20	*EMS3*	*Export market share (% of world exports), in volume – 3-year % change*	
21	*LP1*	*Labour productivity (per hour worked) – 1-year % change*	
22	*CID*	*Core inflation differential vis-à-vis the euro area – pps*	
23	*HHDGDI*	*Household debt including non-profit institutions serving households, consolidated –% of Gross Disposable Income*	
24	*GNPL*	*Gross non-performing loans of domestic and foreign entities – % of gross loans*	

No.	Variable	Description	Thresholds
25	*T1CR*	*Tier-1 capital ratio of banking sector – % of risk-weighted assets*	
26	*ROEBS*	*Return on equity of banking sector – %*	
27	*SHPIR*	*Standardised house price-to-income ratio – % of long-term average (2000 – current)*	
28	*BP*	*Building permits – m² per 1000 inhabitants*	
29	***LTUR***	***Long-term unemployment rate – % of labour force aged 15–74***	
30	***YUR***	***Youth unemployment rate – % of labour force aged 15–24***	
31	***ER***	***Employment rate – % of total population aged 20–64***	
32	***YPEE***	***Young people neither in employment nor in education and training – % of total population aged 15–29***	
33	***PRPE***	***People at risk of poverty or social exclusion – % of total population***	
34	***PRPEST***	***People at risk of poverty after social transfers – % of total population***	
35	***SMDP***	***Severely materially deprived people – % of total population***	
36	***PLH***	***People living in households with very low work intensity – % of total population aged 0–64***	

[*] Social MIP: in bold.

Source: Eurostat 2025.

Appendix 2. Description of social MIP (*auxiliary indicators in italics*)

Social indicator	Description
12. Unemployment rate (% of labour force aged 15–74)	The unemployment rate is the number of people unemployed as a percentage of the labour force. Unemployed persons comprise persons aged 15 to 74 who fulfil all the three following conditions: were not employed during the reference week; are available to start work within the next two weeks following the reference week and have been actively seeking work in the past four weeks preceding the reference week or have already found a job to start within the next three months. The MIP Scoreboard indicator is the number of unemployed persons aged 15–74 as a percentage of the labour force and is calculated as: [U_t / LF_t]. The indicative threshold is 10%.
13. Labour force participation rate (3 y pps change, % of total population aged 15–64 years)	The labour force participation rate is the percentage of economically active population aged 15–64 on the total population of the same age. The International Labour Organisation (ILO) for the purposes of labour market statistics classifies as employed, unemployed and outside the labour force. The economically active population (also called labour force) is the sum of employed and unemployed persons. Persons outside the labour force are those who are neither employed nor unemployed. The MIP Scoreboard indicator is the 3-year change in percentage points, with an indicative threshold of –0.2 pp.

Social indicator	Description
29. Long-term unemployment rate (% of labour force aged 15–74)	*The long-term unemployment rate is the number of persons unemployed for 12 months or longer as a percentage of the labour force (i.e. economically active population aged 15–74).*
30. Youth unemployment rate (% of labour force aged 15–24)	*The youth unemployment rate is the unemployment rate of people aged 15–24 as a percentage of the labour force of the same age.*
31. Employment rate (% of population aged 20–64)	*The employment rate of the total population is calculated by dividing the number of person aged 20 to 64 in employment by the total population of the same age group. The indicator is based on the EU Labour Force Survey.*
32. Young people neither in employment nor in education and training (% of total population aged 15–29)	*The indicator Young people Neither in Employment nor in Education and Training (NEET) provides information on young people (15–29 years) who meet the following two conditions: (a) they are not employed (i.e.źunemployed or inactive according to the ILO), and (b) they have not received any education or training in the four weeks preceding the survey.*
33. People at risk of poverty or social exclusion (% of total population)	*This indicator (AROPE) corresponds to the proportion of persons who are at risk of poverty, or severely materially deprived, or living in households with very low work intensity. Persons are only counted once even if they are present in several sub-indicators.*
34. People at risk of poverty after social transfers (% total population)	*The indicator measures the proportion of persons with an equalised disposable income below the risk-of-poverty threshold, which is set at 60% of the national median equalised disposable income (after social transfers) as a % of total population.*
35. Severely materially and socially deprived people (% total population)	*Severely materially and socially deprived persons have living conditions severely constrained by a lack of resources, such that they experience an enforced lack of at least 7 out of 13 deprivation items: i) capacity to face unexpected expenses, ii) capacity to afford paying for one week annual holiday away from home, iii) capacity to being confronted with payment arrears (on mortgage or rental payments, utility bills, hire purchase instalments or other loan payments), iv) capacity to afford a meal with meat, chicken, fish or vegetarian equivalent every second day, v) ability to keep home adequately, vi) have access to a car/van for personal use, vii) replacing worn-out furniture, viii) having internet connection, ix) replacing worn-out clothes by some new ones, x) having two pairs of properly fitting shoes (including a pair of all-weather shoes), xi) spending a small amount of money each week on him/herself, xii) having regular leisure activities, or xiii) getting together with friends/family for a drink/meal at least once a month.*
36. People living in households with very low work intensity (% of population aged 0–64)	*People living in households with very low work intensity are people aged 0–59 living in households where the adults (aged 18–59) worked less than 20% of their total work potential during the past year. Students are excluded.*

Source: Eurostat 2025.