## Abstract

Traditional labor market indicators capture specific aspects or realities rather than offering an integrated view of its performance. We propose a comprehensive tool to analyze labor market performance, guide policy decision-making, and motivate academic research from a holistic perspective: the Synthetic Labor Market Index (SLMI). The SLMI is a composite indicator formed by 30 variables grouped into four categories: *Unemployment*, *Employment*, *Protection for the Unemployed* and *Salaries*. This paper discusses the SLMI's construction, the results for the case of Spain (2008-2022), and its relationship with other economic indicators. Specifically, we empirically test the validity of the indicator under Okun's Law theoretical background. Our analysis demonstrates the robustness of the SLMI from the methodological and empirical standpoints, which suggests its potential usefulness for academic research and policy formulation. The SLMI proposed by the paper is unprecedented at depicting the labor market in a holistic way

## 1. Introduction

Remunerated work is the main source of household income, which explains the relevance of labor market policies and metrics for researchers, policymakers, and society as a whole. Traditional labor market indicators are no longer capable of explaining labor market dynamics for several reasons.

First, they capture only one dimension of the labor market at a time (employment, unemployment, wages...). Second, labor market complexities have dramatically increased in the last 40 years, making the use of isolated indicators limited and uninformative. For instance, since the 1980s, labor markets in advanced countries have shifted significantly from standard to non-standard forms of employment. Büchtemann and Quack (1990) attribute this shift to the heavy job losses in key industrial sectors and a general employment slowdown since the mid-1970s, leading to a decline in lifelong, full-time jobs and a need for adequate social protection often excluded from collective agreements. More recently, Mellacher (2020) notes that increasing demand for college graduates and the impact of technological advancements have driven wage inequality and altered employment landscapes.

These changes have prompted policies promoting non-standard employment to redistribute opportunities and reduce unemployment. Vosko (2010) adds that non-standard employment disproportionately affects women and marginalized groups, exacerbating existing inequalities and intersecting with gender, citizenship, and labor market regulations. Maloney, Cunningham, and Bosch (2004) highlight that economic crises unevenly impact different households, with vulnerable groups experiencing greater hardships.

In a context like this, it is critical that labor market indicators provide a comprehensive, balanced, and holistic view. Composite indicators address this need by offering a more thorough understanding of labor market dynamics, capturing their complexity in an integrated manner. They also help to reduce the excessive dominance of certain variables that, in the eyes of society, seem to be the only relevant ones for measuring an economic reality. This is the case with the Human Development Index in relation to GDP growth, for example.

Composite indicators, as defined by Freudenberg (2003), are created by combining multiple individual indicators (hereafter base indicators) to measure complex and multidimensional phenomena that single indicators cannot adequately capture. Its increasing significance is evident as their growing utilization suggests, particularly within the public and media realms (Saltelli, 2007). While these measures are widely employed, with the Human Development Index (HDI) serving as a prominent example of this, there has been extensive academic debate surrounding their use. Some researchers warn about the possibility of manipulating the outcomes from the indicator if the procedure to construct it is not transparent (Grupp and Schubert, 2010). Others highlight their ability to garner public interest, simplify the comprehension of intricate and complex phenomena, and energize decision-making processes (Greco et al., 2019).

This paper presents a new composite indicator for monitoring the labor market: the Synthetic Labor Market Index (SLMI). The SLMI aims to capture the diverse dimensions and realities encompassed within the labor market in a rigorous way, providing a more comprehensive view of the labor market than what is offered by single and very dominant variables, such as the unemployment rate or the creation of new jobs. To mitigate the risks associated with the erroneous construction of the index, we have followed the guidelines provided by the OECD (2008) for the development of robust composite indicators.

Literature on the proposal and construction of new indicators requires its validation versus empirical evidence. In this paper, we study the reliability of the SLMI based on Okun's Law Theory (see Prachowny, 1993). Okun's law (Okun, 1962) is an empirical relationship that describes the inverse link between changes in unemployment and economic output.

We test this link for the case of Spain (2008-2022), a country worth scientific study due to its labor market particularities and the need for reform based on a better understanding of its dynamics. Literature has described Spain’s labor market as "dysfunctional" (Bentolila et al., 2012) due to several reasons. First, Spain experiences persistently high unemployment rates. Second, the Spanish labor market faces a duality challenge, as disparities between temporary and permanent contracts complicate the transition from the former to the latter. Third, Spain's labor market regulations have been criticized for being too rigid and burdensome. Finally, Spain faces a significant skills mismatch. This leads to high rates of underemployment and makes it harder for job seekers to find suitable employment (Alvargonzález Muñoz et al., 2022).

Our results show that the proposed SLMI presents a positive correlation with the economic activity variables considered: Synthetic Activity Indicator (SAI), Industrial Production Index (IPI), total vehicle registrations and per capita GDP. The SLMI also demonstrates its efficacy in encapsulating the principal economic events and their repercussions on the Spanish labor market, as well as the “evenness” of labor market performance from the point of view of wages.

This article is structured as follows. Section 2 provides state-of-the-art information on labor market composite indicators. Section 3 outlines the conceptual framework of the SLMI and presents the details of the methodology employed for its construction. Subsequently, Section 4 stresses the outcomes derived from applying the SLMI to the context of Spain and its application to Okun's Law framework. Finally, Section 5 discusses the results and summarizes the main conclusions derived from our analyses.

## 2. Labor Market Composite indicators: state of the art and our proposal

### a. State of the art

In the following paragraphs, we review the literature on composite indicators applied to the labor market, grouping them into thematic clusters: flexibility, employment quality, youth labor market, gender disparities and other fields. We finally introduce our proposal and highlight our contribution to the literature.

Regarding flexibility, Ferent-Pipas (2024) uses an equal-weighted flexicurity composite indicator to examine the relationship between flexicurity and employment inflows in the EU28 countries. Kapitsinis and Gialis (2023) present the Flexible Contractual Arrangements Composite Index (FCACI) to assess work precariousness in EU regions. Gialis and Leontidou (2016) calculate for 12 EU countries the Flexible Contractual Arrangements composite indicator to measure employment flexibility and the Active Labor Market Policies composite indicator to monitor these policies, with a focus on the employability services and the activation measures. Nikulin and Gawrycka (2021) propose a composite indicator to measure the level of flexicurity in European countries.

Davidescu et al. (2020) introduce an employee flexibility indicator that considers different types of flexibility: contractual, functional, working time, and workspace flexibility. Roy et al. (2020) present a state-wise time-variant composite index to account for the stringency of regulation of hiring and firing practices that affect labor adjustment mechanisms in India’s manufacturing sector. In a similar vein, Kawaguchi and Murao (2014) construct a composite index for assessing labor market rigidity.

In terms of employment quality, Farne and Vergara (2015) delve into employment quality in Colombia during the 2002-2011 period, utilizing a composite index constructed through Categorical Principal Components Analysis (CATPCA). Mackett (2020) addresses the measurement of decent work in South Africa by constructing a composite decent work index.

With respect to the literature on the youth labor market and early jobs, the studies of Scandurra et al. (2021) and Cefalo and Scandurra (2021) focus on regional variations in youth labor market integration and introduce a composite indicator known as the Regional Youth Labor Market Integration Index. On a broader scale, Symeonaki et al. (2019) present a multidimensional index of early job insecurity in European countries to capture labor market conditions, job quality, school-to-work transitions, and job security.

Several studies specifically target gender disparities through this methodological approach. Castellano and Rocca (2014) develop a composite indicator to rank European countries based on gender-related labor market dimensions, which has been used and updated by the same authors in former studies (see Castellano and Rocca, 2017, Castellano and Rocca, 2019). Santero-Sanchez et al. (2015) create a job quality index that assesses gender differences in the hospitality industry.

There are also various composite indicators that focus on multiple aspects of the labor market at the same time. Antohi et al. (2023) propose a social security index based on state budgets and demographic indicators. Davidescu (2017) introduces a synthetic measure to track convergence towards the social market economy among EU member states. Lopez-Roldan and Fachelli (2021) introduce a methodology to obtain two synthetic measures of labor market segmentation (one categorical and the other one continuous).

Finally, there are a few examples of composite indicators constructed with a more global and comprehensive perspective. Milanovic et al. (2023) present a composite index designed to evaluate the resilience of labor markets in light of the challenges introduced by COVID-19. While this approach aligns more closely with our objective of providing a holistic assessment of labor market performance, it is limited to the pre-and post-COVID periods and includes only a set of 10 indicators for its construction. Our work goes further by covering a wider time frame and using a broader set of base indicators.

### b. Our proposal

Unlike single-variable indicators, composite indicators are able to capture the complex interplay of various factors and provide a more complete picture of trends and outcomes. Applied to the labor market, the holistic view provided by composite indicators is crucial for identifying underlying trends and patterns that may not be captured by single-variable analyses, like underemployment or stagnant wages, despite rising employment rates. By doing so, they offer nuanced insights essential for effective policy formulation and potentially guide interventions that address specific issues within the labor market. Additionally, the aggregation of base indicators into synthetic ones does not necessarily result in an information loss as they are designed to preserve the distinct contributions of each variable and maintain the richness and detail necessary for thorough analysis.

Composite indicators can also enhance the accuracy of economic forecasting by providing a broad base of data, which is crucial for understanding labor market conditions. They benefit academics and researchers in conducting robust studies and assist firms and policymakers in strategic decision-making.

As shown in the previous section, most of the existing composite indicators applied to the labor market focus on particular dimensions, such as flexicurity, gender inequality or employment quality, without striving for a comprehensive view of labor market performance. This approach overlooks the need for a holistic assessment that encapsulates all facets of the labor market.

In response to this gap, we propose the development of a holistic indicator to measure the overall performance of the labor market, moving beyond the confines of narrowly focused areas. The SLMI is a composite indicator that offers a comprehensive and longitudinal analysis of the labor market. It is made up of 30 base indicators linked to four different categories (*Unemployment, Employment, Protection for the Unemployed and Salaries*) and covers a period of 15 years (2008-2022) with monthly data.

## 3. Methodology

### a. Conceptual Framework

The SLMI captures labor market performance from a four-categories perspective: *Unemployment, Employment, Protection for the Unemployed and Salaries*. Figure 1 provides a structured overview of the categories within the SLMI's conceptual framework. The details on the base indicators within each category (including names and associated alphanumeric code) and their data sources are indicated in Appendix 2. The inclusion criteria prioritize *i)* **reliability**: reliable data from high-quality public sources, focusing on INE (Spanish National Institute of Statistics) and SEPE (Spanish State Public Employment Service) for consistency; *ii)* ***availability*** of indicators for the 2008–2022 period; *iii)* ***monthly updates*** to ensure detailed analysis of trends and fluctuations (while broader data pools from quarterly or yearly sources are considered, their interpolation may reduce accuracy; therefore, only two particularly important quarterly variables have been included: the quarterly employment and unemployment rates); and *iv)* ***clear relevance*** of all indicators to their assigned categories, ensuring alignment with the study's conceptual framework.

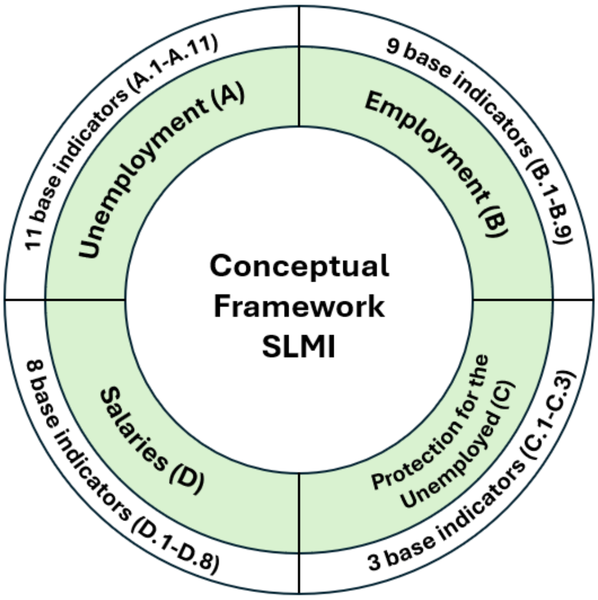


*Figure 1. Conceptual framework of the SLMI*

The *Unemployment* category is composed of 11 base indicators. We include total registered unemployed (A.11), its correction for seasonal variations (A.4) and the unemployment rate (A.10). We also include different variations of the registered unemployment metrics to control for sectorial developments (A.2, A.3, A.5, A.7), gender differences (A.6 and A.9) and the particularities associated with finding a first job (A.1 and A.8). Administrative records indicators (A.1-A.9 and A.11) offer accuracy and detailed longitudinal data, while surveys (published on a quarterly basis, (A.10) provide timeliness and capture informal employment.

The *Employment* category gathers workers' productivity and the type of contracts under which they are being hired through 8 different indicators. We include two types of indicators: registered contracts (total (B.1), with seasonal adjustments (B.3), part-time (B.2) and by contract duration (B.4-B.6)) and productivity measures (per hour (B.7) and full-time equivalent (B.8)). Administrative records (B.1-B.6) are more reliable in covering formal employment, while productivity indicators (B.7 and B.8) offer insights into how workers may benefit from better training, technology, and work environments. Quarterly employment rate (B.9) completes the dataset of the category employment. While the unemployment rate (A.10) reflects the share of the labor force that is unemployed, the employment rate (B.9) shows the proportion of the working-age population that is employed. By combining these indicators, it becomes possible to infer changes in labor force participation and inactivity. For instance, if the unemployment rate decreases but the employment rate remains stable, it likely signals an increase in inactivity, with discouraged workers existing in the labor force.

*Protection for the Unemployed* serves as a measure of the incentives that the public administration provides for labor supply to transform their inactive status into an active one. This category is composed of 3 base indicators that reflect the number of beneficiaries by subsidies' category. Even if literature has shown that higher protection might weaken labor supply and lead to higher inactivity and unemployment rates in the long run (Blanchard and Portugal, 2001), we follow the logic by Farber (1999) to establish a positive relationship between protection and labor market performance through higher jobs' stability (see Hollister, 2011, for further details). The SLMI separates the protection of the unemployed based on whether subsidies are part of welfare programs (C.1) or based on previous contributions from the beneficiaries (C.2-C.3). The former tracks the protection provided by the State to individuals who never joined the labor market or who are affected by long-term unemployment. The latter focuses on short-term unemployment and considers whether workers are receiving the full subsidy or only part of it.

*Salaries* capture labor supply remuneration as well as the cost for the employer of maintaining workers' employment status. It includes 8 different indicators per sector of activity, which allows the SLMI to seize not only the performance of the labor market but also the evolution of households' main income source. We include two categories of variables on salary variation. Wage variation agreed in collective bargaining (D.1) represents the standardized, negotiated outcomes of wage negotiations for a specific group of workers, typically intended to set minimum wage standards and anticipate future conditions. Actual wage changes (D.2-D.8) reflect the real wages workers receive, influenced by market conditions, individual performance, economic factors, and implementation practices.

Overall, the initial set of variables is made up of 30 base publicly available indicators. The decision to use only public datasets was based on the will to make the SLMI replicable and reliable. While private data may have added some granularity, it would have reduced its applicability to other contexts.

### b. Construction of the SLMI

Figure 2 is a flowchart with the steps followed to construct the SLMI (imputation, normalization, multivariate analysis, weighting and aggregation), as well as the software tools used for each step.

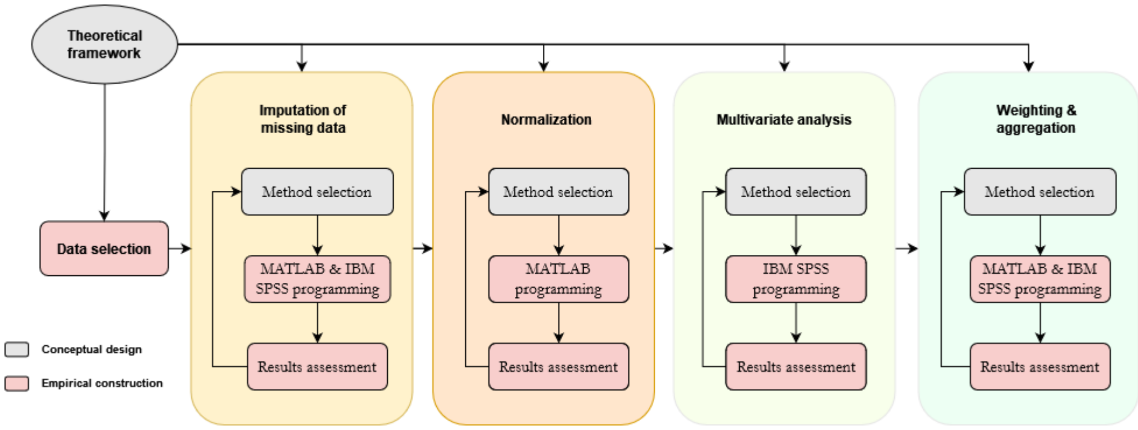


*Figure 2. Construction road map of the SLMI*

After establishing the conceptual framework and selecting the input data/base indicators, it is necessary to perform the imputation of missing observations from base indicators. We have considered two advanced single imputation methods (expectation-maximization and linear regression (OECD, 2008)) and the multiple imputation method through the Markov Chain Monte Carlo (MCMC) (Gold and Bentler, 2000).

Imputation has been applied at the category level, allowing flexibility to select the most appropriate imputation methods for addressing missing data within each specific category. The amount of missing data is slightly above 1%, considering the whole dataset. Therefore, in each category, we apply a test consisting of *i)* hiding 1% of the available information within each base indicator (practically, this implies the deletion of 2 values), *ii)* applying the imputation techniques to fill this missing data, iii) computing at the category level (this is, for all the data imputed within the category) the normalized root mean square error (NRMSE) to assess the degree of similarity between the imputed values and the actual hidden values. The techniques with the best performance regarding the NRMSE were multiple imputation for the *Employment* category and expectation-maximization for the rest[1]. Monthly values of the quarterly indicators (*quarterly unemployment rate* and *quarterly employment rate*) were interpolated.

[1]Nevertheless, since the amount of missing data in the categories is low (1.5% overall, which decomposed by category gives the following figures: 0.2% for *Unemployment*, 1.3% for *Employment*, 1.3% for *Protection for the Unemployed* and 3.6% for *Salaries*) the impact of the imputation method is not expected to be high. This is confirmed by a sensitivity analysis we conducted using a different imputation technique from the selected ones -linear regression- where the variation obtained in the SLMI was only 0.5% on average across the whole time series.

Following this step, normalization was applied with the aim of establishing a common scale for all indicators. Certain methods, such as ranking or standardization, were discarded as they were found unsuitable for subsequent aggregation. The primary concern lies in the challenges robust aggregation methods encounter when handling data transformed through standardization and ranking -specifically, the issues arising from negative values or qualitative-wise data, as discussed in (OECD, 2008)-. Thus, min-max normalization was chosen for its fair replication of distances among data and its fit for aggregation (Talukder et al., 2017).

This method ensures that each base indicator is normalized to a scale ranging from 0 to 100. The lowest value within the time series for each variable is set at 0, representing the worst performance, while the highest value is assigned a score of 100, indicating the best performance. This scale allows for a standardized comparison across all indicators, facilitating an understanding of relative performance over time. Equation (1) has been used for this purpose:

$$I_{it} = \frac{x_{it} - \min\,(x_{it})}{\max\,(x_{it}) - \min(x_{it})} \cdot 100 \tag{1}$$

, where $I_{it}$ stands for the normalized value of indicator $i$ in time $t$ and $x_{it}$ for the original value of indicator $i$ in time $t$.

In the case of the base indicators contained within the *Unemployment* category, their interpretation is not "the higher the value, the better the health of the labor market" but the opposite and, therefore, their normalization must be inverted according to equation (2):

$$I'_{it} = 100 - I_{it} \tag{2}$$

, where ${I_{it}}'$ is the inverted value of $I_{it}$.

By normalizing against the historical maxima and minima, the value of the SLMI indicates how close a given country is, in a given year, to the historical maxima and minima (in the extreme case where the SLMI takes a value of 0/100 for a given year and country, it would mean that for that country, all its base indicators are at their historical minimum/maximum). Nevertheless, the main advantage of using the SLMI (and composite indicators in general) is not the information provided by its absolute value, but the fact that it allows for temporal comparisons (analyzing the historical evolution of the indicator for a given country) and potentially cross-country comparisons.

If we apply the SLMI to more countries, historical maxima and minima of several base indicators might change, affecting the scores, but not the comparison integrity (except if the changes are very pronounced). There are two other options for applying the SLMI to other countries. The first one is to maintain the original maxima and minima, which ensures consistency in Spanish values while requiring saturation to the minimum for those indicators with values lower than that (to avoid negative values after normalization)[2]. The

[2] However, we do not recommend this option in this particular case, as the original sample contains only Spain, making it very likely that many of the minima and maxima could be exceeded by a significant amount.

second one is establishing aspirational goals for normalizing the base indicator. This option enhances the meaningfulness of the SLMI scores since closer proximity to 100 would indicate greater alignment with overarching targets, regardless of the countries or time frame selected. However, this approach requires the participation of numerous experts to establish robust target values, making it a potential area for future research.

After normalization and prior to making decisions on the weighting methods, a multivariate analysis was performed to assess the relationship among base indicators. The first analysis conducted was the computation of the correlation matrices. Depending on the size of the dataset and the level of correlation among base indicators within each category, the analysis could suggest the implementation of statistical weights such as Principal Component Analysis (PCA) or Factor Analysis (FA), whose final suitability will be tested by applying the Kaiser-Meyer-Olkin (KMO) test and the Bartlett's sphericity test (Tabachnick and Fidell, 2013).

On the one hand, the results from the correlation matrix for the categories *Unemployment, Employment,* and *Salaries* -all with eight or more base indicators- revealed significant levels of correlation among the base indicators within the same category, with numerous instances where the Pearson correlation coefficients exceed 0.7. Hence, the application of statistical weights is justified to avoid "double counting" issues (OECD, 2008). As a final verification step to assess the adequacy of the data within these categories for FA, we conducted the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity. For the dataset to be adequate for FA, the result of the KMO test should be above 0.5, and the p-value for Bartlett's sphericity test should be below 0.05 to reject its null hypothesis (Hair et al., 2006). The application of the KMO test to *Unemployment* made it necessary to delete the variable "Registered Unemployment" from the original set of base indicators. After its removal, the KMO test was conducted again and provided a result of 0.564. Moreover, from a conceptual standpoint, all the indicators in this category (see Table A2), delineate unemployment segmented by both sectors and gender. Consequently, omitting the general unemployment indicator will not obscure any crucial information. In the categories *Employment* and *Salaries*, the KMO test showed the data was suitable enough for FA with a KMO test result of 0.683 and 0.795, respectively. The sphericity tests of all the previous categories support KMO test results for applying FA to the dataset.

On the other hand, the application of statistical weights is not recommendable in the category *Protection for the Unemployed*, as it only includes three low correlated indicators.

The final step involves both weighting and aggregation, which can be interpreted as a unified process, as the weighting procedure directly provides the weights applied in the aggregation. As shown in Figure 3, we have chosen a hierarchical aggregation process (bottom-up) with two aggregation levels.

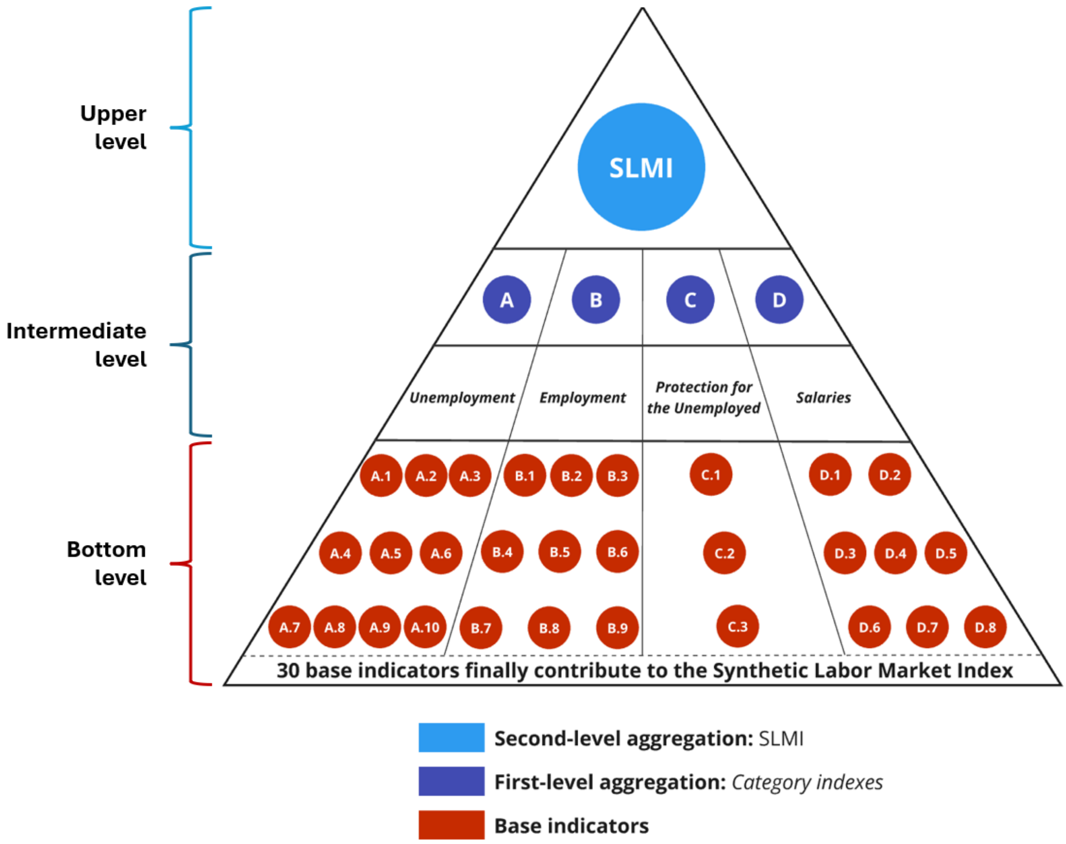


*Figure 3. Hierarchy data structure within the SLMI*

At the bottom level, the base indicators of each category are combined to generate an intermediate 'category index'. The intermediate level of aggregation encompasses the synthesis of all category indexes, culminating in the creation of the SLMI at the upper level. This hierarchical aggregation procedure offers two key advantages: *i)* it helps to mitigate the fungibility issue (Capelle-Blancard and Petit, 2017) by minimizing the possibility of offsetting favorable and unfavorable scores, and *ii)* it guarantees the availability of more detailed measures for enhanced traceability and transparency, facilitating further analysis.

Regarding the weighting techniques, we employed statistical models based on factor analysis (OECD, 2008) for weighting the base indicators within the categories of *Unemployment, Employment,* and *Salaries,* as a result of the multivariate analysis. We detail now the different steps taken in this process. Appendix 1 illustrates the numerical results for the application of this technique to one of these three categories.

1. *Step 1: Obtaining the matrix M of factor loadings.*
   The factor loadings are obtained after applying the PCA with *varimax* rotation to the set of indicators within the category, obtaining a matrix *M* of factor loadings with the structure depicted in (3).

$$M_{[IxF]} = \begin{bmatrix} \lambda_{1,1} & \lambda_{1,2} & \cdots & \lambda_{1,F} \\ \lambda_{2,1} & \lambda_{2,2} & \cdots & \lambda_{2,F} \\ \vdots & \vdots & \lambda_{i,f} & \vdots \\ \lambda_{I,1} & \lambda_{I,2} & \cdots & \lambda_{I,F} \end{bmatrix} \tag{3}$$

where

- $I$ is the number of base indicators within the category studied.
- $F$ refers to the total number of factors within the category, determined by meeting two criteria: *i)* selection of factors with an eigenvalue greater than 1, following the Kaiser criterion (Illahi and Mir, 2021) and *ii)* the cumulative variance explained by the selected factors must account for at least 70%.
- $\lambda_{ij}$ reflects the factor loading of indicator $i$ within factor $f$.

2. *Step 2: Determining the matrix $\bar{M}$ with the percentages of explained variances.*
To compute this matrix $\bar{M}$, it must be noted that the variance associated with a factor $f$ ($\phi_f$) is equal to the sum of all its square factor loadings, as shown in equation (4).

$$\phi_f = \sum_{i=1}^{I} \lambda^2{}_{i,f} \tag{4}$$

Therefore, $\bar{M}$ is computed according to equation (5)

$$\bar{M}_{[IxF]} = \begin{bmatrix} \frac{\lambda^2{}_{1,1}}{\sum_{i=1}^{I} \lambda^2{}_{i,1}} & \frac{\lambda^2{}_{1,2}}{\sum_{i=1}^{I} \lambda^2{}_{i,2}} & \cdots & \frac{\lambda^2{}_{1,F}}{\sum_{i=1}^{I} \lambda^2{}_{i,F}} \\ \frac{\lambda^2{}_{2,1}}{\sum_{i=1}^{I} \lambda^2{}_{i,1}} & \frac{\lambda^2{}_{2,2}}{\sum_{i=1}^{I} \lambda^2{}_{i,2}} & \cdots & \frac{\lambda^2{}_{2,F}}{\sum_{i=1}^{I} \lambda^2{}_{i,F}} \\ \vdots & \vdots & \frac{\lambda^2{}_{i,f}}{\sum_{i=1}^{I} \lambda^2{}_{i,f}} & \vdots \\ \frac{\lambda^2{}_{I,1}}{\sum_{i=1}^{I} \lambda^2{}_{i,1}} & \frac{\lambda^2{}_{I,2}}{\sum_{i=1}^{I} \lambda^2{}_{i,2}} & \cdots & \frac{\lambda^2{}_{I,F}}{\sum_{i=1}^{I} \lambda^2{}_{i,F}} \end{bmatrix} = \begin{bmatrix} \frac{\lambda^2{}_{1,1}}{\phi_1} & \frac{\lambda^2{}_{1,2}}{\phi_2} & \cdots & \frac{\lambda^2{}_{1,F}}{\phi_F} \\ \frac{\lambda^2{}_{2,1}}{\phi_1} & \frac{\lambda^2{}_{2,2}}{\phi_2} & \cdots & \frac{\lambda^2{}_{2,F}}{\phi_F} \\ \vdots & \vdots & \frac{\lambda^2{}_{i,f}}{\phi_f} & \vdots \\ \frac{\lambda^2{}_{I,1}}{\phi_1} & \frac{\lambda^2{}_{I,2}}{\phi_2} & \cdots & \frac{\lambda^2{}_{I,F}}{\phi_F} \end{bmatrix} \tag{5}$$

3. *Step 3: Determining the two relative weights of base indicator i ($\sigma_i$ and $w_i$)*
Each base indicator must be assigned to a single factor. Specifically, it is assigned to the factor for which the indicator shows the highest percentage of explained variance. Consequently, the value of $\sigma_i$ corresponds to the highest percentage of explained variance for the base indicator $i$ among all factors and is computed according to equation (6). The value of $w_i$ corresponds to the variance explained by the factor to which it has been assigned and is computed according to equation (7).

$$\sigma_i = \max\left(\frac{\lambda^2{}_{i,1}}{\phi_1}, \frac{\lambda^2{}_{i,2}}{\phi_2}, \ldots, \frac{\lambda^2{}_{i,F}}{\phi_F}\right) \tag{6}$$

$$w_i = \frac{\phi_j}{\sum_{f=1}^{F} \phi_f}, j \in \{1,2, \ldots F\} \; such \; that \; \frac{\lambda^2{}_{i,j}}{\phi_j} = \sigma_i \tag{7}$$

4. *Step 4: Obtaining the total weight for base indicator i ($\tau_i$ )*

The total weight associated with the base indicator $i$ is obtained by multiplying both relative weights, as shown in equation (8).

$$\tau_i = \sigma_i \cdot w_i \qquad (8)$$

Since relative weight $\sigma_i$ represents the percentage of the variance explained by indicator $i$ within the assigned factor, and relative weight $w_i$ represents the percentage of the variance explained by the factor assigned to base indicator $i$ (with respect to the total variance explained by all the factors), multiplying both relative weights provides the overall variance explained by base indicator $i$ in the assigned factor.

5. *Step 5: Determining the final weight for base indicator i to unity sum ($\alpha_i$ )*
Since the variance explained by indicator $i$ in the other factors is not observed, the sum of all $\tau_i$ within the category is not equal to 1 ($\sum_{i=1}^{I} \tau_i < 1$). Thus, to obtain the final weight $\alpha_i$ the correspondent total weight must be scaled to unity sum, as shown in equation (9).

$$\alpha_i = \frac{\tau_i}{\sum_{i=1}^{I} \tau_i} \qquad (9)$$

Since there are various categories and the weights are given to each indicator within each category, in the rest of the paper the total weight assigned to a base indicator $i$ within category $k$ will be labeled as $\alpha_{k,i}$ (this notation adds only one subindex compared to that in equation (9)).

In the case of the category *Protection for the Unemployed* (category C), we applied equal weighting considering that the 3 base indicators reflect similar protection measures in terms of both quantitative and qualitative impact for the unemployed ($\alpha_{C,i} = 1/3$).

In the second level of aggregation, we applied a participatory weighting approach, particularly the Budget Allocation Process (BAP) (Greco et al., 2019), also referred to as expert criteria. This approach is suitable due to the small number of indicators to be aggregated -the use of the BAP is not recommended when the number of indicators exceeds 10, as it may introduce inconsistencies (OECD, 2008)- and, mainly due to the lack of correlation among category indexes from the conceptual point of view. The weights assigned to each category $k$ will be labeled as $\beta_k$.

*Unemployment, Employment*, and *Salaries* (categories A, B and D) have been assigned a weight of 30% each one ($\beta_A = \beta_B = \beta_D$), since we consider the three of them to play an equal role in the determination of the overall performance of the labor market. *Unemployment* and *Employment* weights together represent 60% of the total, as they are the two main ways that economic analysis has to capture the outputs and equilibrium of any labor market. *Salaries* (30%) are one of the most relevant drivers of labor supply (see Creedy and Duncan, 2002 and Howell et al., 2007 for more details), especially compared to *Protection for the Unemployed* (category C), which has been assigned a weight of 10% ($\beta_C = 0.1$). Thus, we hypothesize that labor supply characteristics are more relevant to determining workers' and potential workers' behavior than activation policies. The equal weights strategy, which dominates most of the literature on synthetic indicators, has been ruled out, as assigning excessive weight to the *Protection for the Unemployed* category could introduce a conceptual imbalance in the SLMI and disproportionately penalize the index during periods of strong labor market performance.

Concerning aggregation, we apply different techniques depending on the level of substitutability (trade-off allowance) considered at each aggregation level. We identify two levels of substitutability from the set of three substitutability scenarios documented by Lafortune et al. (2018):

- Absolute substitutability, for which the regression in one indicator can be counterbalanced by the progress of another one. The corresponding aggregation method for this level of substitutability is a linear aggregation, also known as weighted mean (see equation (10)).

$$CI_t = \sum_i \alpha_i \cdot I_{it} \tag{10}$$

  , where $CI_t$ stands for the composite indicator for a time $t$, $\alpha_i$ reflects the weight of indicator $i$ and $I_{it}$ represents the normalized value of indicator $i$ in time $t$.

- Intermediate substitutability is employed to aggregate heterogeneous variables in cases where only a certain, but not absolute, trade-off is accepted. The associated aggregation method for this level of substitutability is geometric aggregation (see equation (11)).

$$CI_t = \prod_i I_{it}^{\alpha_i} \tag{11}$$

Given the aforementioned rationale, arithmetic aggregation is suited for the first level of aggregation since the substitutability among base indicators is high and the potential risk of interdependence among them has been addressed through multivariate analysis and the careful selection of weighting techniques. Conversely, at the second level of aggregation, we permit only intermediate substitutability among categories and apply the geometric aggregation.

Equation (12) shows the final formula to compute the SLMI for time $t$ ($SLMI_t$):

$$SLMI_t = \prod_{k \in \{A,B,C,D\}} \left( \left( \sum_{i \in S(k)} \alpha_{k,i} \cdot I_{it} \right)^{\beta_k} \right) \tag{12}$$

where:

- $A, B, C, D$ correspond with the four categories observed (*Unemployment, Employment, Protection for the Unemployed,* and *Salaries,* respectively)
- $S(k)$ corresponds with the set of base indicators within category $k$.
- $\alpha_{k,i}$ corresponds with the weight for base indicator $i$ within category $k$ (obtained with factor analysis in categories $A, B, D$ and with equal weighting in category $C$).
- $\beta_k$ corresponds with the weight for category $k$ (obtained with BAP).

## 4. Results

### a. Synthetic Labor Market Index

Figure 4-Panel A depicts the SLMI and the main events that affected the Spanish labor market during the time frame considered. Figure 4-Panel B presents the evolution of each of the SLMI components. This is the first time that a composite labor market indicator covers such a long period of time (15 years) with this frequency (monthly update).

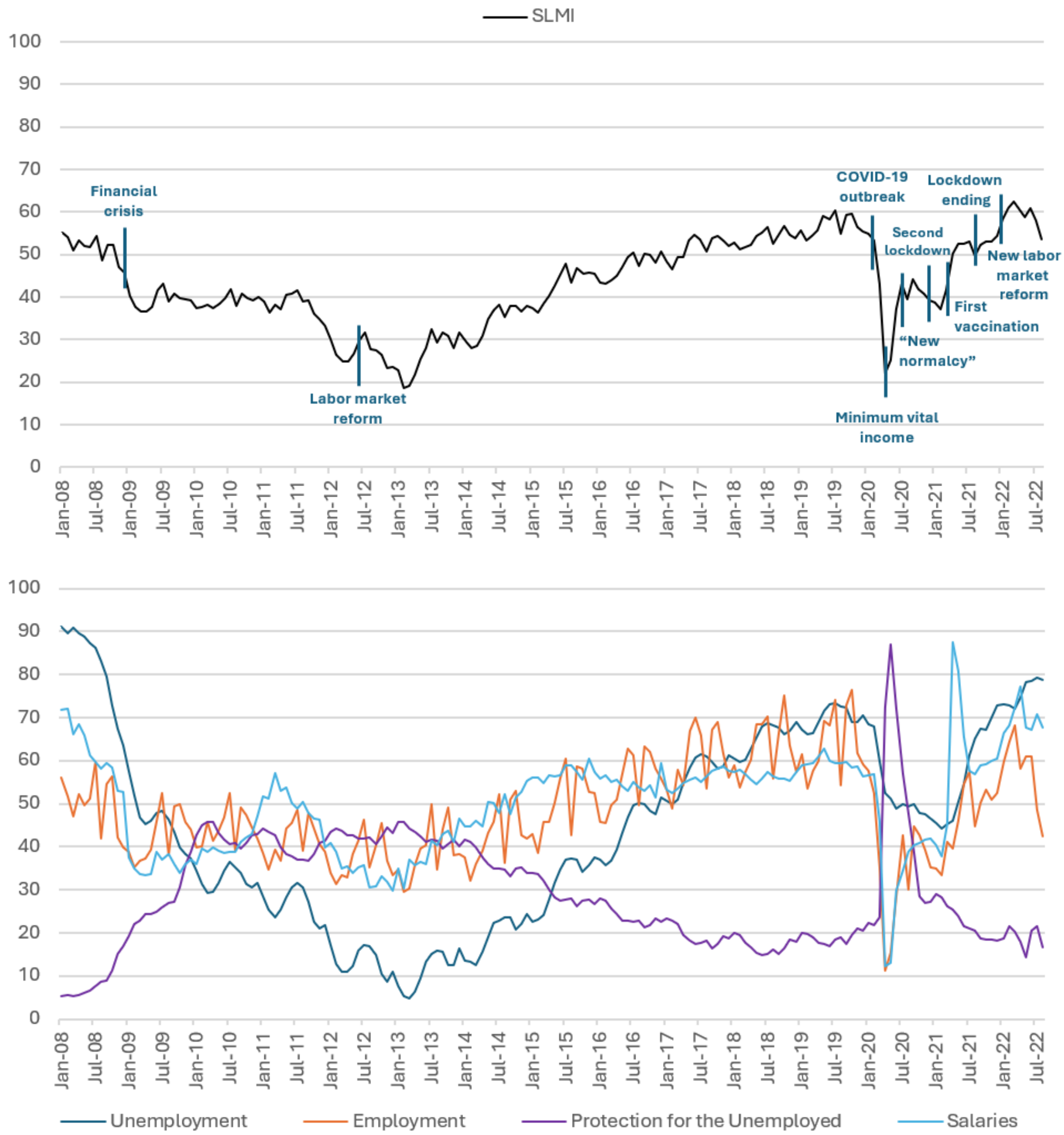


*Figure 4. Temporal evolution of the SLMI and its categories linked to main economic Spanish events*

We can observe three periods in the evolution of the SLMI. The first one covers the months prior to the 2007-2008 financial crisis until the approval of the labor market reform of the year 2012. In that first stage, the labor market showed a clear deterioration (the SLMI fell from more than 50 to below 25 points) due to the sovereign crisis that hit Spain between 2010 and 2013. Higher unemployment and lower wages explain this outcome.

The second stage goes from that moment to the outburst of the COVID-19 pandemic. The Spanish labor market experienced a constant improvement across those years. According to the evolution of the SLMI, it almost tripled from slightly above 20 to almost 60 points in March 2020. The country experienced a period of relatively robust job creation, even if youth unemployment and temporary employment contracts remained a concern.

Finally, the third stage goes from March 2020 to the latest available data point. In March 2020, Spain, like many other countries, imposed strict lockdown measures to contain the spread of COVID-19. This led to a severe economic downturn, resulting in the sharp increase in unemployment captured by the SLMI.

The Spanish government implemented various measures to mitigate the economic impact of the pandemic. As the pandemic was brought under control and restrictions were eased, there was a gradual recovery in the labor market. Employment grew, and even if the post-COVID crisis resulted in a new SLMI maximum (again above 60 points), Spain was still grappling with structural labor market issues, including a high degree of temporary employment. The pandemic exacerbated income and stability disparities as captured by the SLMI which approached the 50-point level again.

As it can be observed in Figure 4-Panel B, three of the four categories within the SLMI (*Unemployment, Employment,* and *Salaries*) follow the same 3-stages evolution of the aggregate indicator. *Protection for the Unemployed* behaves in a countercyclical way, as expected[3], since it is a policy variable whose effect smooths the SLMI. Actually, the smoother evolution of the SLMI compared with the *Employment* and *Unemployment* categories is driven by the inclusion of this category.

The visualization of the evolution of the different categories within the SLMI helps to understand its general performance. For example, the seasonal effect of registered *Employment* gets muted by the stability of other categories, such as *Protection for the Unemployed* or *Salaries*. This can also be found in the pre-and post-pandemic periods. The dramatic fall experienced by the SLMI in March and April 2020 and the subsequent recovery are driven by the *Unemployment* and *Employment* categories. Despite the increase in the *Protection for the Unemployed* category during this period, it was not strong enough to prevent the SLMI from losing around 30 points between its 2020 peak and bottom.

### b. Okun's Law: Interactions with significant economic indicators

In this section, we present the relationships between the SLMI and four relevant economic activity indicators: the SAI, the IPI, the number of vehicle registrations, and per capita GDP. Additionally, we test the evolution of the SLMI versus labor costs' variation to control for the balanced and even evolution of the labor market.

For the evaluation of a given country's potential output, Okun (1962) analyzed the relationship between economic activity and unemployment. He argued against the concept

[3] Given the normalization process applied to the base indicators within each category, a higher value in the category-level indicator represents a better performance.

of the "highest level of production" in favor of the concept of "full employment," which he defined as the level of employment in the absence of inflationary pressures.

Figure 5 relates the SLMI with the four economic activity indicators considered in the study, where a min-max normalization was applied to them for comparability purposes:

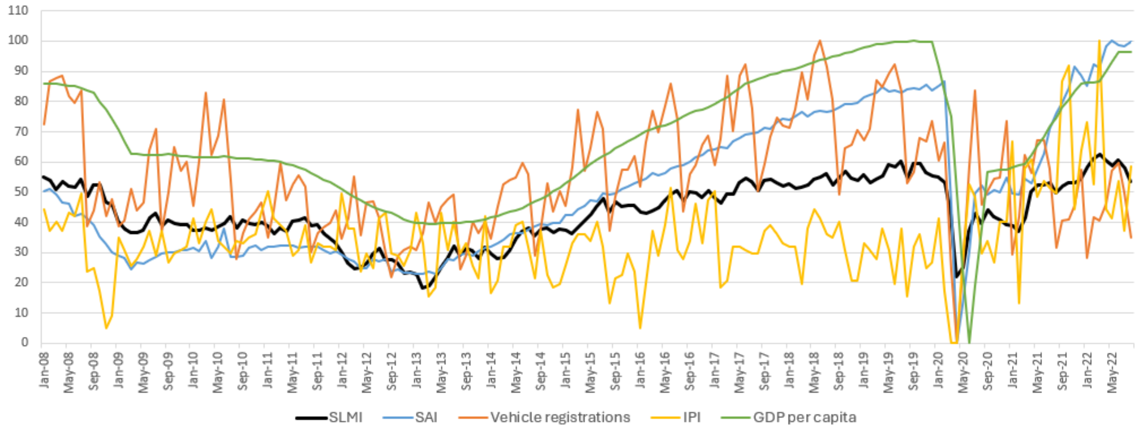


*Figure 5. Normalized indicators considered in the study*

SAI is an indicator published monthly by the Spanish Ministry of Economic Affairs and Digital Transformation. It is a composite indicator that follows economic activity through the information provided by several indicators (total sales in large companies tourist arrivals, etc.)[4]

IPI is a short-term measure of the monthly evolution of the productive activity of the industrial branches, excluding construction, contained in the National Classification of Economic Activities 2009 (CNAE-2009)[5].

New vehicle registrations capture the number of cars and motorcycles inscribed in Spanish registers in a given month; it is a commonly used macroeconomic indicator to evaluate the situation of one of the most important categories under the Gross Fixed Capital Formation (GFCF) umbrella.

SAI, IPI, vehicle registrations and per capita GDP behave in a similar way during the observed period, as can be seen in Figure 5. From 2008 to 2014, they show a weak performance driven by the financial and sovereign crises and their aftermath. The 2014 to 2020 period covers the subsequent recovery until the COVID crisis. From 2020 to 2023, COVID's impact and its repercussions can be easily observed. IPI stands as the only exception, as it only experiences two differentiated stages. The first one, from 2008 to 2020, is characterized by the stability of industrial production. The second one, from the COVID crisis onward, exhibits robust growth.

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[4] See https://portal.mineco.gob.es/es-es/economiayempresa/EconomiaInformesMacro/Documents/Documentos%20Metodol%C3%B3gicos/Metodologia%20de%20los%20indicadores%20sint%C3%A9ticos.pdf for further methodological details.

[5] See https://www.ine.es/daco/daco43/metoipi21.pdf for further methodological details.

As mentioned in the Introduction, we have selected Okun's Law as it is a well-established labor market theory whose characteristics and nuances have been widely explored. Okun (1962) suggested the existence of a negative relationship between unemployment and output. Literature has empirically tested this through different methodologies. Originally, Okun focused on the difference between unemployment and the natural unemployment rate as the dependent variable and the difference between the actual output and the potential output as the independent variable. This is known as the "gap approach."

Knotek (2007) tested that relationship with two additional variations. The first one, formally known as the "dynamic" approach, models the relationship between changes in unemployment rates and changes in real GDP growth over time. Unlike the gap formulation, it incorporates lagged effects and recognizes that the impact of changes in economic output on unemployment may take some time to fully materialize. The second one, labeled as the "difference" approach, rather than focusing on the gap between actual and natural unemployment rates, looks at the changes in these variables to determine the relationship between them.

The "difference" approach offers several advantages over the "gap" and "dynamic" approaches. First, it focuses on changes rather than on absolute levels, which reduces measurement errors and data inconsistencies. Second, it offers a straightforward interpretation, as a one-percentage-point increase in the unemployment rate is associated with a certain change in the growth rate. This makes it easier for policymakers and analysts to understand and communicate the subsequent economic implications. Finally, it does not require assumptions about data stationarity, which makes it more flexible and adaptable to different analytical needs.

Consequently, we test the relationship between the SLMI and the four selected economic activity indicators through the "difference" approach on a monthly basis (Louail and Benarous, 2021). Our application is stated by equation (13):

$$\Delta U_t = \beta_0 + \beta_1 \cdot \Delta Y_t \tag{13}$$

where $\Delta U_t$ stands for the monthly change in the SLMI in time $t$ and $\Delta Y_t$ stands for the monthly change in the economic index (SAI, IPI, vehicle registrations or per capita GDP) in time $t$.

We use the original series for the estimation of the parameters in equation (13). The smoothing effect of anti-seasonality transformations (such as the Hodrick-Prescott filter) would mask certain fluctuations not driven by seasonal patterns, such as those connected with the COVID-19 crisis[6]. Tables 1-4 show the results of the different estimates of the Okun Law model. As has been already mentioned, we test the relationship of the SLMI with SAI, IPI, vehicle registrations and per capita GDP.

[6] The models with the HP filters have also been tested, and the results are consistent.

| *N=175* | Coefficient | Std. error | t-ratio | p-value |
|---|---|---|---|---|
| **Constant** | -0.1011 | 0.1962 | -0.5152 | 0.6071 |
| **Var. SAI** | 0.3281*** | 0.0349 | 9.3990 | 0.0000 |

| | | | |
|---|---|---|---|
| Mean dependent var | -0.0089 | S.D. dependent var. | 3.1763 |
| Sum squared resid. | 1162.103 | S.E. of regression | 2.5918 |
| R-squared | 0.3380 | Adjusted R-squared | 0.3342 |
| F (1,173) | 88.3387 | P-value (F) | 0.0000 |
| Log-likelihood | -413.9693 | Akaike criterion | 831.9386 |
| Schwarz criterion | 838.2682 | Hannan-Quinn | 834.5061 |

*** statistically significant at a significance level of 1%

*Table 1. Okun's Law relating the Synthetic Activity Index and the Synthetic Labor Market Index*

| *N=175* | Coefficient | Std. error | t-ratio | p-value |
|---|---|---|---|---|
| **Constant** | -0.0145 | 0.2297 | -0.0630 | 0.9499 |
| **Var. IPI** | 0.0680*** | 0.0165 | 4.1300 | 0.0001 |

| | | | |
|---|---|---|---|
| Mean dependent var | -0.0089 | S.D. dependent var. | 3.1763 |
| Sum squared resid. | 1597.9510 | S.E. of regression | 3.0392 |
| R-squared | 0.0897 | Adjusted R-squared | 0.0845 |
| F (1,173) | 17.0575 | P-value (F) | 0.0001 |
| Log-likelihood | -441.8372 | Akaike criterion | 887.6745 |
| Schwarz criterion | 894.0040 | Hannan-Quinn | 890.2419 |

*** statistically significant at a significance level of 1%

*Table 2. Okun's Law relating the Industrial Production Index and the Synthetic Labor Market Index*

| *N=175* | Coefficient | Std. error | t-ratio | p-value |
|---|---|---|---|---|
| **Constant** | 0.0145 | 0.2104 | 0.0688 | 0.9452 |
| **Var. vehicle registrations** | 0.1088*** | 0.0149 | 7.3260 | 0.0000 |

| | | | |
|---|---|---|---|
| Mean dependent var | -0.0089 | S.D. dependent var. | 3.1763 |
| Sum squared resid. | 13339.8060 | S.E. of regression | 2.7829 |
| R-squared | 0.2368 | Adjusted R-squared | 0.2324 |
| F (1,173) | 53.6766 | P-value (F) | 0.0000 |
| Log-likelihood | -426.4199 | Akaike criterion | 856.8399 |
| Schwarz criterion | 863.1695 | Hannan-Quinn | 859.4074 |

*** statistically significant at a significance level of 1%

*Table 3. Okun's Law relating the number of vehicle registrations and the Synthetic Labor Market Index*

| *N=57* | Coefficient | Std. error | t-ratio | p-value |
|---|---|---|---|---|
| **Constant** | 0.1448 | 0.5366 | 0.2698 | 0.7883 |
| **Var. GDP per capita** | 0.1500*** | 0.0400 | 3.7500 | 0.0004 |

| | | | |
|---|---|---|---|
| Mean dependent var | 0.1723 | S.D. dependent var. | 4.4983 |
| Sum squared resid. | 902.3686 | S.E. of regression | 4.0505 |
| R-squared | 0.2037 | Adjusted R-squared | 0.1892 |
| F (1,173) | 14.0659 | P-value (F) | 0.0004 |
| Log-likelihood | -159.5957 | Akaike criterion | 323.1914 |
| Schwarz criterion | 327.2775 | Hannan-Quinn | 324.7794 |

*** statistically significant at a significance level of 1%

*Table 4. Okun's Law relating the change in GDP per capita and the Synthetic Labor Market Index*

Our findings suggest that there exists a positive correlation between the variation of economic activity (represented by SAI, IPI, number of vehicles registered and per capita GDP) and labor market performance, captured by the SLMI[7]. This fits in Okun's Law literature estimations, which indicates that our indicator is capable of capturing not only economic activity evolution but also the "quality" of that growth.

Beyond the application of the SLMI to Okun's Law theoretical framework, we test the validity of the synthetic indicator as a tool to capture other labor market features. We develop this robustness check with labor costs, measured as the amount paid by an employer to cover an employee's wages and benefits, plus related payroll taxes and benefits. Table 5 shows the obtained results.

We find a positive and significant association between both variables, which allows us to infer that the SLMI not only "captures" variations of economic activity, but also its evenness and the balanced evolution of the labor market from the point of view of labor costs.

| *N=57* | Coefficient | Std. error | t-ratio | p-value |
|---|---|---|---|---|
| **Constant** | 0.0970 | 0.5819 | 0.1667 | 0.8682 |
| **Var. labor costs** | 5.2485* | 2.6395 | 1.9880 | 0.0517 |

| | | | |
|---|---|---|---|
| Mean dependent var | 0.1717 | S.D. dependent var. | 4.4983 |
| Sum squared resid. | 1057.1450 | S.E. of regression | 4.3842 |
| R-squared | 0.0671 | Adjusted R-squared | 0.0501 |
| F (1,173) | 3.9539 | P-value (F) | 0.0517 |
| Log-likelihood | -164.1074 | Akaike criterion | 332.2147 |
| Schwarz criterion | 336.3008 | Hannan-Quinn | 333.8027 |

* statistically significant at a significance level of 10%

*Table 5. Labor costs and the Synthetic Labor Market Index*

[7] Since the intercepts were not significant, we re-estimated the models without them, and the results obtained are consistent.

## 5. Discussion and Conclusions

Academic and policy interest in labor market metrics has clearly grown in the last few years. This paper shows, however, that traditional labor market metrics should be complemented with the elaboration and publication of composite indicators. Such indicators distill complex information into straightforward, informative, and comprehensive metrics, facilitating a broader understanding among stakeholders.

This paper proposes a new composite indicator, the SLMI, capable of capturing labor market performance from a broad perspective. Particularly, it includes 30 variables from different key aspects of the labor market, categorized into four categories: *Unemployment*, *Employment, Protection for the Unemployed* and *Salaries*.

The main hypothesis that this paper tests is whether the SLMI is capable of explaining the evolution of labor market performance from the broadest possible perspective and not from a rather specific one (gender inequality, jobs quality...), as much of the literature does. We test the validity of the SLMI for the case of Spain for a period of almost 15 years, with robust and literature-aligned results.

On the one hand, the SLMI shows a positive correlation with the economic activity variables analyzed. Specifically, when Okun's Law is applied to the SLMI, it reveals a positive relationship with all of them. The precise extent to which every variable behaves due to the situation of the labor market is left for further research.

On the other hand, the SLMI also proved to be capable of capturing the main economic events and their impact on the Spanish labor market for the considered period. It also reflects the balanced evolution of the labor market from the point of view of wages.

The SLMI can contribute to a more coherent policy design as it provides a more comprehensive vision than individual indicators and composite labor market indicators existing in the literature. It also helps to identify trends and emerging issues and prevents conflicting policies. It fosters a balanced approach to labor market regulation, considering trade-offs between flexibility, security, employment growth, and wage fairness.

From the point of view of monitoring and evaluation, it promotes transparency and accountability. At the same time, it can contribute to setting realistic benchmarks to develop more complex impact assessments of policy changes.

The SLMI also allows for permanent updates through the inclusion of new variables related to current events or concerns, as well as those whose access may transition from initially restricted to public in the future. This is, at the same time, one of the main strengths and limitations of our proposal. We acknowledge the value of expanding the scope of our analysis in future research to incorporate new and emerging factors. Some potential variables that could be considered in future studies include the separation of employment, unemployment, and wages indicators by educational level. These metrics can provide deeper insights into how different educational groups are affected by labor market dynamics, for instance.

Average matching times between labor supply and demand would also contribute to understanding the efficiency of job-matching processes and reveal sector-specific dynamics and potential areas for policy intervention. Potential inclusions should aim to keep the informative capacity of the indicator as stable as possible without altering its core meaning or societal interpretation; otherwise, they risk losing credibility and comprehensibility.

The design of the SLMI allows for the relative importance of its components to vary depending on the country where it is applied or the phase of the economic cycle. For example, during periods of economic downturn, greater emphasis *on Protection for the Unemployed* might be necessary, while in times of economic expansion, categories such as *Salaries* or *Employment* could play a more prominent role. Future research should focus on developing dynamic adjustment mechanisms for the weights of the SLMI, prioritizing approaches that are as automatic and responsive as possible. These mechanisms could be data-driven, incorporating macroeconomic indicators or labor market trends to ensure the index remains adaptable and reflective of the specific conditions in which it is utilized.

The SLMI aids in targeted resource allocation, informed business and investment decisions, and tailored educational and training programs. It also provides a comprehensive view of labor market health, guiding policymakers in designing effective interventions that promote economic stability, social equity, and public trust.

**CONFLICT OF INTEREST STATEMENT**

On behalf of all authors, the corresponding author states that there is no conflict of interest.

**DATA AVAILABILITY STATEMENT**

We use public data, specifying the databases in the manuscript.

**DECLARATION OF AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS**

During the preparation of this work, the authors used ChatGPT to improve readability and language, not to replace key researcher tasks such as interpreting data or drawing scientific conclusions. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

## Appendix 1: Supplementary material on statistical weighting

This section provides a complete example of the calculations computed in each of the steps defined in section 3B, involving equations (3) to (9), to obtain the weights for all the base indicators within the *Employment* category (the order of the base indicators in the matrices below (each one in a row) is exactly the same as in Table A2). The application to the other two categories where this technique is used follows the same process.

*Step 1: Obtaining the matrix $M$ of factor loadings*

$$M_{[9x3]}=\begin{bmatrix}\lambda_{1,1}&\lambda_{1,2}&\lambda_{1,3}\\ \lambda_{2,1}&\lambda_{2,2}&\lambda_{2,3}\\ \lambda_{3,1}&\lambda_{3,2}&\lambda_{3,3}\\ \lambda_{4,1}&\lambda_{4,2}&\lambda_{4,3}\\ \lambda_{5,1}&\lambda_{5,2}&\lambda_{5,3}\\ \lambda_{6,1}&\lambda_{6,2}&\lambda_{6,3}\\ \lambda_{7,1}&\lambda_{7,2}&\lambda_{7,3}\\ \lambda_{8,1}&\lambda_{8,2}&\lambda_{8,3}\\ \lambda_{9,1}&\lambda_{9,2}&\lambda_{9,3}\end{bmatrix}=\begin{bmatrix}0.9456&-0.0786&0.2398\\ 0.9047&-0.0520&0.1990\\ 0.7981&-0.2937&0.2639\\ 0.1749&-0.0349&0.8179\\ 0.4443&0.7285&0.1509\\ 0.9612&-0.0578&0.0001\\ -0.3206&0.6866&-0.1643\\ -0.2471&0.8500&-0.1106\\ 0.1283&-0.0810&0.8207\end{bmatrix}$$

Notes:

i) Factor loadings with Varimax rotation have been computed with SPSS software

ii) The number of indicators within this category is eight ($I=9$) and the number of factors complying with the selection criteria (eigenvalue greater than 1, and cumulative variance accounting for at least 70%) is two ($F=3$).

*Step 2: Determining the matrix $\bar{M}$ with the percentages of explained variances**

$$\phi_{f=1}=\sum_{i=1}^{9}\lambda^2{}_{i,1}=3.682\quad(52.0\%\ of\ total\ variance\ explained)$$
$$\phi_{f=2}=\sum_{i=1}^{9}\lambda^2{}_{i,2}=1.831\quad(25.8\%\ of\ total\ variance\ explained)$$
$$\phi_{f=3}=\sum_{i=1}^{9}\lambda^2{}_{i,3}=1.571\quad(22.2\%\ of\ total\ variance\ explained)$$

$$\bar{M}_{[9x3]}=\begin{bmatrix}\frac{\lambda^2{}_{1,1}}{\phi_1}&\frac{\lambda^2{}_{1,2}}{\phi_2}&\frac{\lambda^2{}_{1,3}}{\phi_3}\\ \frac{\lambda^2{}_{2,1}}{\phi_1}&\frac{\lambda^2{}_{2,2}}{\phi_2}&\frac{\lambda^2{}_{2,3}}{\phi_3}\\ \frac{\lambda^2{}_{3,1}}{\phi_1}&\frac{\lambda^2{}_{3,2}}{\phi_2}&\frac{\lambda^2{}_{3,3}}{\phi_3}\\ \frac{\lambda^2{}_{4,1}}{\phi_1}&\frac{\lambda^2{}_{4,2}}{\phi_2}&\frac{\lambda^2{}_{4,3}}{\phi_3}\\ \frac{\lambda^2{}_{5,1}}{\phi_1}&\frac{\lambda^2{}_{5,2}}{\phi_2}&\frac{\lambda^2{}_{5,3}}{\phi_3}\\ \frac{\lambda^2{}_{6,1}}{\phi_1}&\frac{\lambda^2{}_{6,2}}{\phi_2}&\frac{\lambda^2{}_{6,3}}{\phi_3}\\ \frac{\lambda^2{}_{7,1}}{\phi_1}&\frac{\lambda^2{}_{7,2}}{\phi_2}&\frac{\lambda^2{}_{7,3}}{\phi_3}\\ \frac{\lambda^2{}_{8,1}}{\phi_1}&\frac{\lambda^2{}_{8,2}}{\phi_2}&\frac{\lambda^2{}_{8,3}}{\phi_3}\\ \frac{\lambda^2{}_{9,1}}{\phi_1}&\frac{\lambda^2{}_{9,2}}{\phi_2}&\frac{\lambda^2{}_{9,3}}{\phi_3}\end{bmatrix}=\begin{bmatrix}\mathbf{0.24}&0.00&0.04\\ \mathbf{0.22}&0.00&0.03\\ \mathbf{0.17}&0.05&0.04\\ 0.01&0.00&\mathbf{0.43}\\ 0.05&\mathbf{0.29}&0.01\\ \mathbf{0.25}&0.00&0.00\\ 0.03&\mathbf{0.26}&0.02\\ 0.02&\mathbf{0.39}&0.01\\ 0.00&0.00&\mathbf{0.43}\end{bmatrix}$$

**The bold represents the factor (column) assigned to each indicator (row)*

*Step 3: Determining the two relative weights of base indicator $i$ ($\sigma_i$ and $w_i$)*

$$\begin{bmatrix}\sigma_1\\ \sigma_2\\ \sigma_3\\ \sigma_4\\ \sigma_5\\ \sigma_6\\ \sigma_7\\ \sigma_8\\ \sigma_9\end{bmatrix}=\begin{bmatrix}\max\left(\frac{\lambda^2{}_{1,1}}{\phi_1},\frac{\lambda^2{}_{1,2}}{\phi_2},\frac{\lambda^2{}_{1,3}}{\phi_3}\right)\\ \max\left(\frac{\lambda^2{}_{2,1}}{\phi_1},\frac{\lambda^2{}_{2,2}}{\phi_2},\frac{\lambda^2{}_{2,3}}{\phi_3}\right)\\ \max\left(\frac{\lambda^2{}_{3,1}}{\phi_1},\frac{\lambda^2{}_{3,2}}{\phi_2},\frac{\lambda^2{}_{3,3}}{\phi_3}\right)\\ \max\left(\frac{\lambda^2{}_{4,1}}{\phi_1},\frac{\lambda^2{}_{4,2}}{\phi_2},\frac{\lambda^2{}_{4,3}}{\phi_3}\right)\\ \max\left(\frac{\lambda^2{}_{5,1}}{\phi_1},\frac{\lambda^2{}_{5,2}}{\phi_2},\frac{\lambda^2{}_{5,3}}{\phi_3}\right)\\ \max\left(\frac{\lambda^2{}_{6,1}}{\phi_1},\frac{\lambda^2{}_{6,2}}{\phi_2},\frac{\lambda^2{}_{6,3}}{\phi_3}\right)\\ \max\left(\frac{\lambda^2{}_{7,1}}{\phi_1},\frac{\lambda^2{}_{7,2}}{\phi_2},\frac{\lambda^2{}_{7,3}}{\phi_3}\right)\\ \max\left(\frac{\lambda^2{}_{8,1}}{\phi_1},\frac{\lambda^2{}_{8,2}}{\phi_2},\frac{\lambda^2{}_{8,3}}{\phi_3}\right)\\ \max\left(\frac{\lambda^2{}_{9,1}}{\phi_1},\frac{\lambda^2{}_{9,2}}{\phi_2},\frac{\lambda^2{}_{9,3}}{\phi_3}\right)\end{bmatrix}=\begin{bmatrix}0.24\\ 0.22\\ 0.17\\ 0.43\\ 0.29\\ 0.25\\ 0.26\\ 0.39\\ 0.43\end{bmatrix};$$

$$\begin{bmatrix}w_1\\ w_2\\ w_3\\ w_4\\ w_5\\ w_6\\ w_7\\ w_8\end{bmatrix}=\begin{bmatrix}\frac{\phi_j}{\sum_{f=1}^{2}\phi_f},j\ \in\{1,2,3\}\ such\ that\ \frac{\lambda^2{}_{1,j}}{\phi_j}=\sigma_1\\ \frac{\phi_j}{\sum_{f=1}^{2}\phi_f},j\ \in\{1,2,3\}\ such\ that\ \frac{\lambda^2{}_{2,j}}{\phi_j}=\sigma_2\\ \frac{\phi_j}{\sum_{f=1}^{2}\phi_f},j\ \in\{1,2,3\}\ such\ that\ \frac{\lambda^2{}_{3,j}}{\phi_j}=\sigma_3\\ \frac{\phi_j}{\sum_{f=1}^{2}\phi_f},j\ \in\{1,2,3\}\ such\ that\ \frac{\lambda^2{}_{4,j}}{\phi_j}=\sigma_4\\ \frac{\phi_j}{\sum_{f=1}^{2}\phi_f},j\ \in\{1,2,3\}\ such\ that\ \frac{\lambda^2{}_{5,j}}{\phi_j}=\sigma_5\\ \frac{\phi_j}{\sum_{f=1}^{2}\phi_f},j\ \in\{1,2,3\}\ such\ that\ \frac{\lambda^2{}_{6,j}}{\phi_j}=\sigma_6\\ \frac{\phi_j}{\sum_{f=1}^{2}\phi_f},j\ \in\{1,2,3\}\ such\ that\ \frac{\lambda^2{}_{7,j}}{\phi_j}=\sigma_7\\ \frac{\phi_j}{\sum_{f=1}^{2}\phi_f},j\ \in\{1,2,3\}\ such\ that\ \frac{\lambda^2{}_{8,j}}{\phi_j}=\sigma_8\\ \frac{\phi_j}{\sum_{f=1}^{2}\phi_f},j\ \in\{1,2,3\}\ such\ that\ \frac{\lambda^2{}_{9,j}}{\phi_j}=\sigma_9\end{bmatrix}=\begin{bmatrix}\frac{\phi_1}{\phi_1+\phi_2+\phi_3}\\ \frac{\phi_1}{\phi_1+\phi_2+\phi_3}\\ \frac{\phi_1}{\phi_1+\phi_2+\phi_3}\\ \frac{\phi_3}{\phi_1+\phi_2+\phi_3}\\ \frac{\phi_2}{\phi_1+\phi_2+\phi_3}\\ \frac{\phi_1}{\phi_1+\phi_2+\phi_3}\\ \frac{\phi_2}{\phi_1+\phi_2+\phi_3}\\ \frac{\phi_2}{\phi_1+\phi_2+\phi_3}\\ \frac{\phi_3}{\phi_1+\phi_2+\phi_3}\end{bmatrix}=\begin{bmatrix}0.52\\ 0.52\\ 0.52\\ 0.22\\ 0.26\\ 0.52\\ 0.26\\ 0.26\\ 0.22\end{bmatrix}$$

*Step 4: Obtaining the total weight for base indicator $i$ ($\tau_i$)*

$$\begin{bmatrix}\tau_1\\ \tau_2\\ \tau_3\\ \tau_4\\ \tau_5\\ \tau_6\\ \tau_7\\ \tau_8\\ \tau_9\end{bmatrix}=\begin{bmatrix}\sigma_1\cdot w_1\\ \sigma_2\cdot w_2\\ \sigma_3\cdot w_3\\ \sigma_4\cdot w_4\\ \sigma_5\cdot w_5\\ \sigma_6\cdot w_6\\ \sigma_7\cdot w_7\\ \sigma_8\cdot w_8\\ \sigma_9\cdot w_9\end{bmatrix}=\begin{bmatrix}0.13\\ 0.12\\ 0.09\\ 0.09\\ 0.07\\ 0.13\\ 0.07\\ 0.10\\ 0.10\end{bmatrix}$$

*Step 5: Determining the final weight for base indicator $i$ to unity sum ($\alpha_i{}^*$)*

$$\begin{bmatrix}\alpha_1\\ \alpha_2\\ \alpha_3\\ \alpha_4\\ \alpha_5\\ \alpha_6\\ \alpha_7\\ \alpha_8\\ \alpha_9\end{bmatrix}=\begin{bmatrix}0.14\\ 0.13\\ 0.10\\ 0.11\\ 0.08\\ 0.15\\ 0.07\\ 0.11\\ 0.11\end{bmatrix}$$

** Since the category selected for this example is Employment (category B), $\alpha_i$ is labelled as $\alpha_{B,i}$ in equation (12).*

# Appendix 2: Supplementary table on the SLMI's weights

| | Base indicators | Loadings from factor 1 ($\lambda_{1,i}$) $\phi_1$ = 5.012 | Loadings from factor 2 ($\lambda_{2,i}$) $\phi_2$ = 4.697 | $\sigma$ | $w$ | $\tau$ | $\alpha$ |
|---|---|---|---|---|---|---|---|
| **Unemployment *(A)*** $\beta_A$ = 30% | Registered unemployment (<25 years)[1] (A.1) | 0.231 | 0.949 | 0.192 | 0.484 | 0.093 | 0.112 |
| | Registered unemployment Agriculture and fisheries[1] (A.2) | 0.978 | -0.133 | 0.191 | 0.516 | 0.099 | 0.119 |
| | Registered unemployment Construction[1] (A.3) | 0.049 | 0.996 | 0.211 | 0.484 | 0.102 | 0.123 |
| | Registered unemployment CVE[1] (A.4) | 0.759 | 0.639 | 0.115 | 0.516 | 0.059 | 0.072 |
| | Registered unemployment Industry[1] (A.5) | 0.244 | 0.965 | 0.198 | 0.484 | 0.096 | 0.116 |
| | Registered unemployment Women[1] (A.6) | 0.933 | 0.345 | 0.174 | 0.516 | 0.090 | 0.108 |
| | Registered unemployment Services[1] (A.7) | 0.950 | 0.269 | 0.180 | 0.516 | 0.093 | 0.112 |
| | Registered unemployment No previous employment[1] (A.8) | 0.854 | 0.422 | 0.145 | 0.516 | 0.075 | 0.091 |
| | Registered unemployment Men[1] (A.9) | 0.585 | 0.808 | 0.139 | 0.484 | 0.067 | 0.081 |
| | Quarterly unemployment rate[1] (A.10) | 0.721 | 0.652 | 0.104 | 0.516 | 0.054 | 0.065 |
| | Registered unemployment[1] (A.11) | --- | --- | --- | --- | --- | --- |

| | Base indicators | Loadings from factor 1 ($\lambda_{1,i}$) $\phi_1$ = 3.682 | Loadings from factor 2 ($\lambda_{2,i}$) $\phi_2$ = 1.831 | Loadings from factor 3 ($\lambda_{3,i}$) $\phi_3$ = 1.571 | $\sigma$ | $w$ | $\tau$ | $\alpha$ |
|---|---|---|---|---|---|---|---|---|
| **Employment *(B)*** $\beta_B$ = 30% | Registered contracts[1] (B.1) | 0.946 | -0.079 | 0.2398 | 0.243 | 0.520 | 0.126 | 0.141 |
| | Part-time Registered contracts[1] (B.2) | 0.905 | -0.052 | 0.199 | 0.222 | 0.520 | 0.116 | 0.129 |
| | CVE Registered contracts[1] (B.3) | 0.798 | -0.294 | 0.264 | 0.173 | 0.520 | 0.090 | 0.100 |
| | Indefinite Registered contracts[1] (B.4) | 0.175 | -0.035 | 0.818 | 0.426 | 0.222 | 0.094 | 0.106 |
| | Interim Registered contracts[1] (B.5) | 0.444 | 0.729 | 0.151 | 0.290 | 0.258 | 0.075 | 0.084 |
| | Temporary Registered contracts[1] (B.6) | 0.961 | -0.058 | 0.001 | 0.251 | 0.520 | 0.130 | 0.146 |
| | Productivity per hour actually worked[1] (B.7) | -0.321 | 0.687 | -0.164 | 0.258 | 0.258 | 0.067 | 0.074 |
| | Productivity per full-time job[1] (B.8) | -0.247 | 0.850 | -0.111 | 0.395 | 0.258 | 0.102 | 0.114 |
| | Quarterly employment rate[1] (B.9) | 0.128 | -0.0810 | 0.821 | 0.429 | 0.222 | 0.095 | 0.106 |

| | Base indicators | $\alpha$ |
|---|---|---|
| **Protection for the Unemployed *(C)*** $\beta_C$ = 10% | Welfare beneficiaries[2] (C.1) | 0.333 |
| | Contributory benefits partial unemployment[2] (C.2) | 0.333 |
| | Contributory benefits total unemployment[2] (C.3) | 0.333 |

| | Base indicators | Loadings from factor 1 ($\lambda_{1,i}$) $\phi_1$ = 5.019 | Loadings from factor 2 ($\lambda_{2,i}$) $\phi_2$ = 1.459 | $\sigma$ | $w$ | $\tau$ | $\alpha$ |
|---|---|---|---|---|---|---|---|
| **Salaries *(D)*** $\beta_D$ = 30% | Wage increase agreed in collective bargaining[1] (D.1) | -0.006 | -0.815 | 0.456 | 0.225 | 0.103 | 0.108 |
| | Year-on-year variation of labor income Agriculture[1] (D.2) | 0.308 | 0.750 | 0.386 | 0.225 | 0.087 | 0.092 |
| | Year-on-year variation of labor income Trade[1] (D.3) | 0.965 | 0.074 | 0.186 | 0.775 | 0.144 | 0.151 |
| | Year-on-year variation of labor income Constructions[1] (D.4) | 0.821 | 0.337 | 0.134 | 0.775 | 0.104 | 0.110 |
| | Year-on-year variation of labor income Hospitality[1] (D.5) | 0.772 | 0.105 | 0.119 | 0.775 | 0.092 | 0.097 |
| | Year-on-year variation of labor income Industry[1] (D.6) | 0.903 | 0.246 | 0.163 | 0.775 | 0.126 | 0.133 |
| | Year-on-year variation of labor income Services[1] (D.7) | 0.974 | 0.092 | 0.189 | 0.775 | 0.147 | 0.154 |
| | Year-on-year variation of labor income Total[1] (D.8) | 0.978 | 0.179 | 0.191 | 0.775 | 0.148 | 0.156 |

*Table A2. Weights to compute the SLMI*

1. The data of the base indicator was obtained from the National Institute of Statistics (INE, 2023).
2. The data of the base indicator was obtained from the Public Service of State Employment (SEPE, 2023).

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