Economic Analysis

Mexico: New Labor Market Stress and Performance Index

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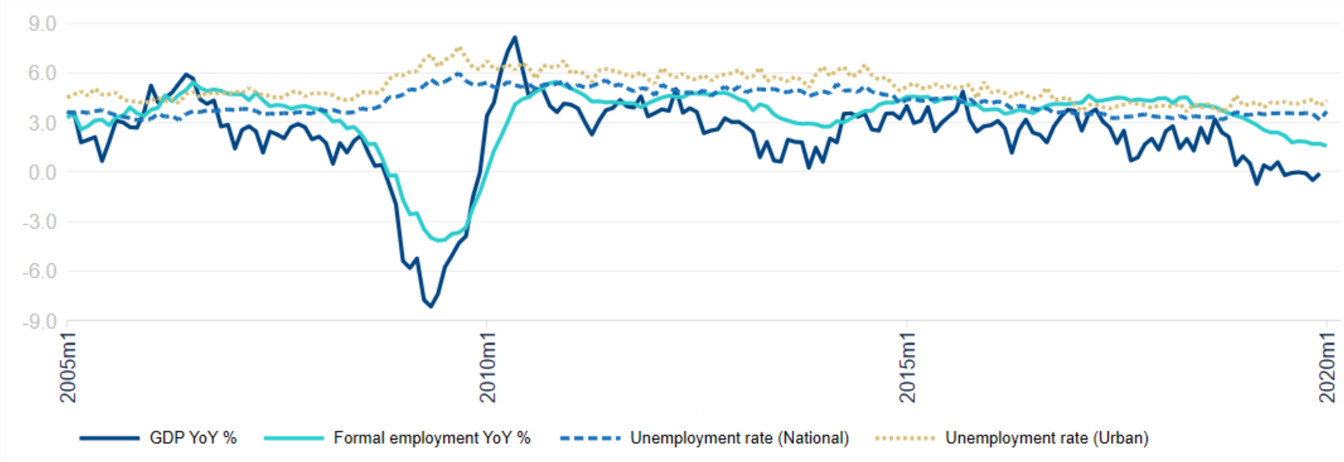
March 5, 2020

Labor Market and Economic Activity in Mexico

The labor market in Mexico is characterized by a heterogeneous structure and behavior, with segments that operate similarly to the competitive market and other, unstructured segments with high rigidity (Cervantes A., 2017). Furthermore, one of the most important features that characterize the Mexican labor market is the high level of informal employment, with more than half of self-employed or subordinate employment falling under this category.

In this context, when carrying out an analysis of labor dynamics, it is necessary to take into account different indicators that allow a better understanding of the behavior of the labor market (Islas Camargo & Cortez, 2013), as the failure to do so may lead to biased interpretations or conclusions. For example, comparing the unemployment rate and the annual variations in GDP, Graph 1 shows that the annualized GDP rate has a much higher variability related to the unemployment rate. In particular, the coefficient of variation for annual GDP rates is 1.22, compared to the coefficient of variation (CV) for the unemployment rate that is just 0.18.

Graph 1. **MEXICO: GROSS DOMESTIC PRODUCT (GDP), FORMAL EMPLOYMENT AND UNEMPLOYMENT RATE** (% MONTHLY FIGURES, 2005–2019)



Source: BBVA Research, IMSS and INEGI

This situation becomes more evident still when comparing previous rates and those from the 2009 crisis; in the case of GDP, the average annual growth rates were 2.7% and -4.5%, respectively and, by contrast, the unemployment rate showed more stable behavior with average rates of 3.5% before the crisis and 5.2% during the crisis. This has raised some doubts regarding the correct measurement of unemployment in Mexico: How can unemployment levels, which are even lower than in countries with a higher level of development, be explained in a context of low economic growth? We consider that one of the reasons why the unemployment rate exhibits lower variance than GDP, and at a lower correlation than that observed in other countries, is the importance of the informal sector acting as a buffer in the face of economic slowdown or contraction scenarios in which formal employment falls.

The difficulty in answering this question has called into question the reliability of employment statistics, which are calculated in accordance with the methodological criteria and definitions of the International Labor Organization (ILO) (Heath, 2012). As a result, various research projects and, in particular, a broad analysis on labor market indicators by the National Institute of Statistics and Geography of Mexico (*Instituto Nacional de Estadística y Geografía, INEGI*), concluded that analysis of the labor market must take into account different complementary indicators that provide a broader view of its short- and long-term changes.

Based on the above, the aim of this document is to propose a Labor Market Stress and Performance Index (LM-SPI) that captures the variability and stresses present in the labor market regarding access to employment and job creation. The LM-SPI will enable us to identify changes in short-term labor dynamics and their trends at both a national and urban level.

Labor Market Indicators

Indicators that take into account specific characteristics of the labor environment in terms of supply, demand and structure have been developed and standardized to carry out labor market analysis and monitoring. In Mexico, and largely as a result of the debate over the apparent low correlation between economic growth and the unemployment rate, work has been done to develop indicators to better measure changes in the labor market. As a result of this need, INEGI developed and published up to 17 indicators that are complementary to the unemployment rate, including measures similar to the complementary unemployment rates measured in the United States (Heath, 2012). The conclusion of these measures is that, in most cases, there is a high correlation with the unemployment rate, thus the contributions for labor market analysis were very low, which is why several of these indicators were no longer measured.

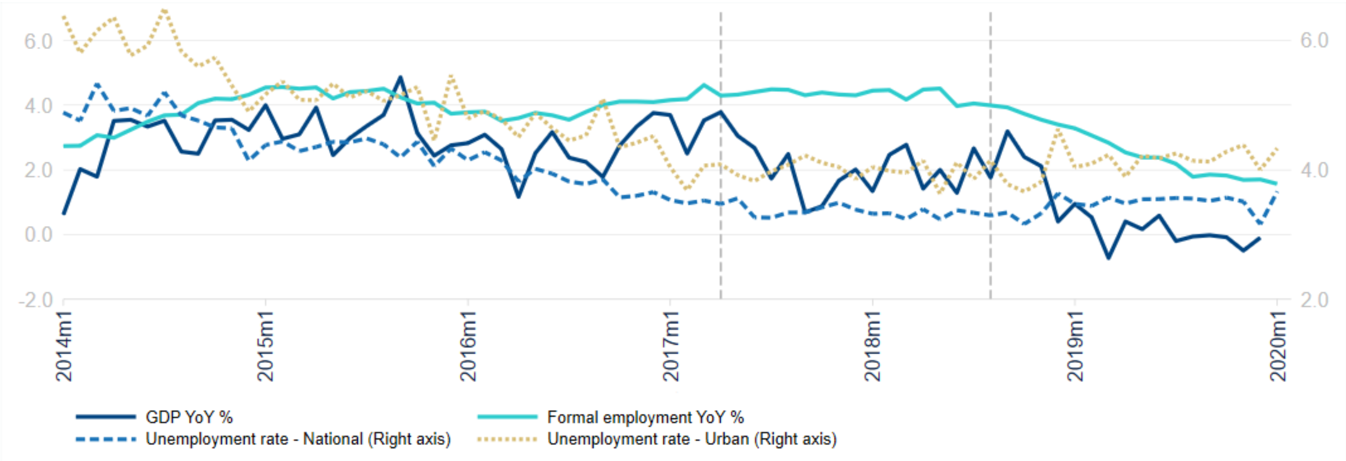
After the INEGI rate refinement process and with the standardization of measurements obtained from the National Survey of Occupation and Employment (ENOE) as the only source, a series of indicators have been created within which we located the following rates related to access to employment and job creation: 1) unemployment rate, 2) partial occupation rate and unemployment rate, 3) general pressure rate, 4) underemployment rate, and 5) occupation rate in the informal sector.

In addition to these indicators, another relevant source of information on the labor market is the formal employment registry based on insured salaried workers registered by the Mexican Social Security Institute (*Instituto Mexicano del Seguro Social, IMSS*). This indicator is highly relevant because it enables us to have a precise understanding of the dynamics of formal job creation, and, as can be seen in Graph 1, it has high synchrony—much higher than the unemployment rate—with economic dynamics in most of the series.

Despite formal employment showing itself to be highly related to economic dynamics, this indicator cannot be taken on its own as a unique reference for labor market dynamics due to three elements: 1) changes in measurement methodology, 2) it does not capture formal public employment, and 3) it is highly sensitive to the implementation of public policies. An example of this last point was the employment formalization program implemented in July 2013, which consisted of reducing informality by promoting the formalization of salaried workers of medium and large formal enterprises not registered with social security; this led to an increase in formal employment stemming from the number of jobs registered with IMSS and not through the creation of new jobs, thus distorting the relationship between these two variables.

The result of the formalization program can be seen in Graph 2, where, from 2014 onward, there is a break in the synchrony between the annual formal employment growth rate and GDP. This became more evident in the 2017 to 2018 period, where GDP saw high variability and, in contrast, formal employment growth remained virtually constant at annual growth rates of more than 4%. During this period, the efforts to formalize the federal government intensified, creating a desynchronization that negatively impacted the relevance of this indicator for correct identification of the dynamics of new job creation, thus losing its efficiency as a thermometer to measure labor market conditions. As a result of the foregoing, the joint analysis of these indicators better shows labor market dynamics, which makes the construction of the LM-SPI more relevant.

Graph 2. **MEXICO: GROSS DOMESTIC PRODUCT (GDP), FORMAL EMPLOYMENT AND UNEMPLOYMENT RATE** (% MONTHLY FIGURES, 2014–2019)



Source: BBVA Research, IMSS and INEGI

Data

For the estimation of the LM-SPI, four labor market rates published by INEGI and the IMSS job creation variable were used as a reference. Variable selection was carried out based on three criteria:

1. Measurement frequency. Monthly periodicity that enables monthly monitoring of the indicator
2. Simplicity. Conceptually, these rates are measured periodically by INEGI and additional indicators do not need to be calculated, which, in turn, facilitates their reproducibility
3. Consistency. Measurement is consistent over the long term and comes from virtually the same source of information

It should be noted that all of the included rates are from seasonally adjusted series and in addition, in the case of urban rates, an aggregation of 32 cities is taken as reference[1].

1: INEGI. https://www.inegi.org.mx/contenidos/programas/enoe/15ymas/doc/con_basedatos_proy2010.pdf

Specifically, the indicators used to estimate the index are the following:

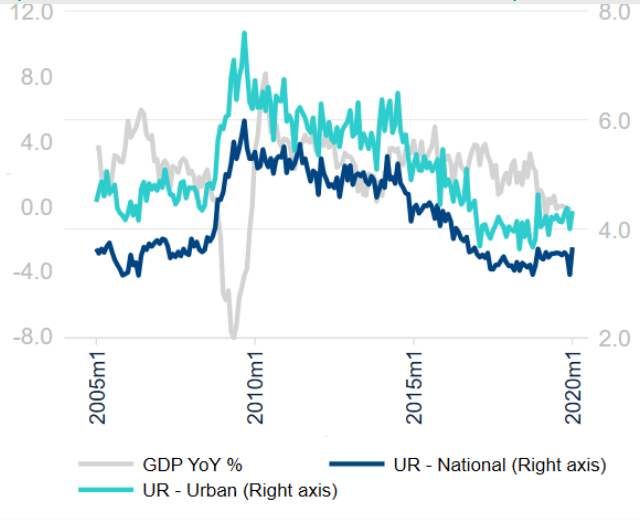
01	Unemployment rate (UR)	Percentage of the economically active population (EAP) aged 15 and over that is unemployed and that searched for work in the reference week because they were not linked to an economic activity or a job.
02	General pressure rate (GPR)	Percentage representing the unemployed population, plus the employed population looking for work, in relation to the economically active population (EAP).
03	Underemployment rate (UER)	Percentage of the employed population that has the need and availability to offer more working time than their current occupation allows. Includes those who work less than 35 hours per week for market purposes.
04	Labor informality rate (LIR)	Proportion of the working population that is vulnerable due to the nature of the economic unit in which they work, where their link or employee status is not recognized by their source of work.
05	Formal employment - IMSS (FE)	Persons affiliated with the IMSS associated with a job. Persons affiliated with more than one employer are counted as many times as the number of jobs they hold.

All of these indicators refer to the dynamics of access to employment and job creation. The unemployment, general pressure, and underemployment rates show stresses related to available jobs, i.e., they reflect the employment needs of both the unemployed and the employed. On the other hand, the absorptive capacity of available jobs is approached from formal IMSS employment and from the occupation in the informal sector as a negative or distorting element of labor market pressure; i.e., by limiting access to formal employment, people tend to work in the informal sector, and thus, taking it into account complements the understanding of labor market dynamics.

Estimation of the index began in 2005 with the start of the ENOE series, which is a standardized and homogeneous source on the labor market with monthly and quarterly data. Prior to this year, employment measurements came from different sampling frameworks and sources, which limits a longer historical series from being used. It is important to note that ENOE quarterly employment figures are more accurate; in this case, the quarterly data has a sampling error of 3%, which in the case of the monthly data is 6%. This is explained by the fact that monthly information is derived from one-third of the quarterly sample. Despite the preceding, monthly data is most useful for the analysis of the current situation, which is why it is used to estimate the index.

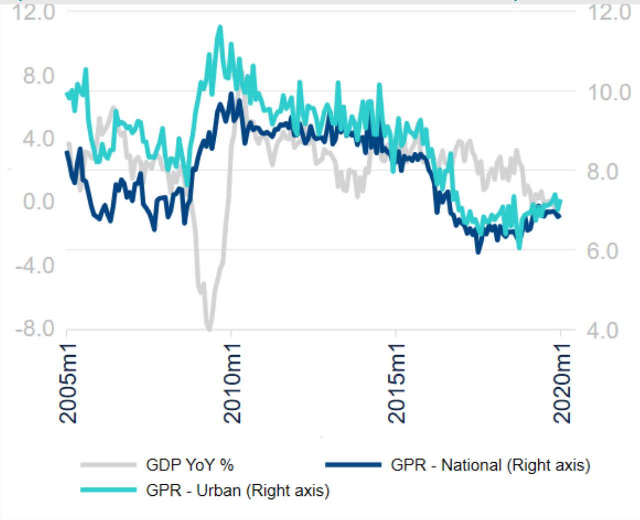
The unemployment rate is an indicator that is negatively correlated with economic activity but with low sensitivity. During the period between 2005 and 2008, the rate demonstrated stable and lagged behavior with respect to economic activity. It is clear that in May 2009 during the global economic crisis, the GDP had a negative growth of less than 9.26 pp compared to the previous year. In contrast, the national unemployment rate for these same periods only increased by 2 pp. In the United States, in contrast, the growth rate fell by 2.5 pp that same year, while the unemployment rate rose to 9.9% from the levels of around 5% before the onset of the crisis. One notable aspect of unemployment rates is that their behavior shows much higher variability at the urban level than at the national level, thus they are much more sensitive to changes in the labor market in the short term — see Graph 3. This presumably occurs because the informality rate is lower in urban environments.

Graph 3. **UNEMPLOYMENT RATE**
(% WITH RESPECT TO THE TOTAL EAP)



Source: BBVA Research, IMSS and INEGI

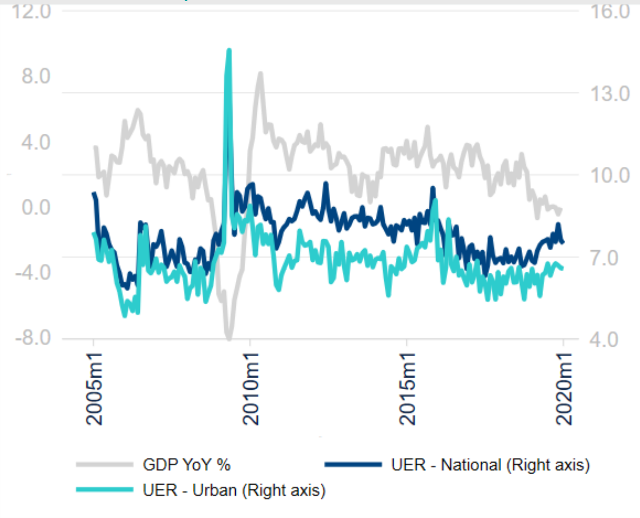
Graph 4. **GENERAL PRESSURE RATE (GPR)**
(% WITH RESPECT TO THE TOTAL EAP)



Source: BBVA Research, IMSS and INEGI

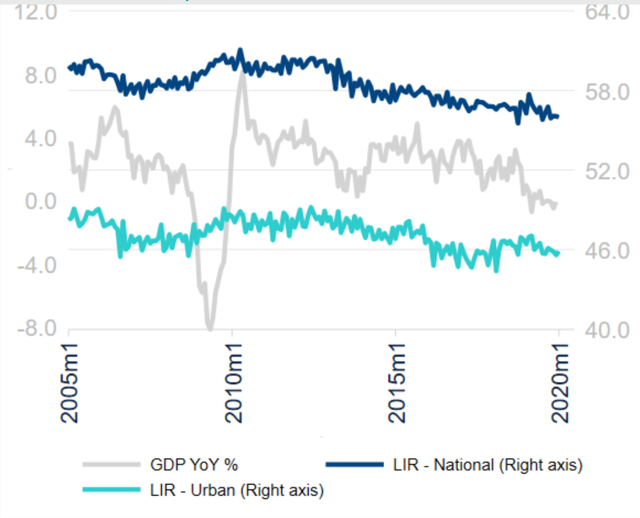
The pressure rate shows a high correlation with the unemployment rate, and thus, a negative correlation with economic activity. This rate includes unemployed and employed job seekers, which is why it tends to show higher levels. In May 2009, which was the peak of GDP decline, the seasonally adjusted general pressure rate reached 8.9% nationally and the urban rate reached 10.9%. On the other hand, a negative correlation also prevails in the underemployment and informality rates, i.e., informality and underemployment rates tend to fall at higher levels of activity.

Graph 5. **UNDEREMPLOYMENT RATE**
(% WITH RESPECT TO THE TOTAL EMPLOYED POPULATION)



Source: BBVA Research, IMSS and INEGI

Graph 6. **LABOR INFORMALITY RATE**
(% WITH RESPECT TO THE TOTAL EMPLOYED POPULATION)



Source: BBVA Research, IMSS and INEGI

The formal job creation rate is the variable with the closest correlation with GDP in the long term; in a first exploratory analysis of data, the correlation between annual rates of formal employment and GDP was 0.99 — see Table 1.

Table 1. **CORRELATIONS BETWEEN GDP AND SELECTED LABOR MARKET VARIABLES**

Variables in logarithms	GDP	L3.GDP	L6.GDP	L9.GDP
UR s.a.	-0.2881	-0.2917	-0.2817	-0.2708
GPR s.a.	-0.4361	-0.4455	-0.4453	-0.4407
UER s.a.	-0.1594	-0.1575	-0.1318	-0.1185
LIR s.a.	-0.7816	-0.7939	-0.7970	-0.7916
FE s.a.	0.9914	0.9928	0.9915	0.9885

Source: BBVA Research, IMSS and INEGI
s.a. Seasonally adjusted.
L. Lag operator

Methodology and Estimation of the Index

To estimate the index, a factor analysis was performed with the aim to simplify relationships that may exist between the observed variables. That is why this analysis attempts to find common dimensions or factors which are not directly observable and which sufficiently explain the observed variables with as little information loss as possible and facilitating their joint interpretation. One of the properties of this methodology is that it implies the existence of a latent or synthetic variable that can be explained from a dataset, for which a model is constructed that enables the identification of factors that explain the interrelationships between the variables.

Factor analysis takes total variance as a reference and estimates the factors that contain low proportions of the unique variance and, specifically, extracts the overall variance from a correlation matrix. Based on the above, the commonalities between variables with shared or common variance are obtained.

The number of factors is determined by extracting combinations of variables that explain the highest percentage of variance and finding the combinations of factors that explain the amount of variance from highest to lowest.

Estimation of the index was based on observable variables as stationary variables by defining the following factorial model:

Variables = { D.(log(UR)) = X1, D.(log(GPR)) = X2, D.(log(UER) = X3, D.(log(LIR)) = X4, D.(1/FE_YoY%) = X5}

In which:

D - First difference operator
log - logarithm

With the exception of formal employment, the variables are standardized in logarithms and in first differences, which allows us first to stabilize variance and, on the other hand, to work with stationary series. In addition, and to make the index consistent, we worked with the inverse of the first difference for the annual growth rate of the FE variable; in this sense, it is assumed that when the inverse of the annual rate increases, there is greater pressure on the labor market.

The estimated factor model is as follows:

$$X_1 = l_{11}F_1 + l_{12}F_2 + \cdots + l_{1k}F_k + e_1$$
$$X_2 = l_{21}F_1 + l_{22}F_2 + \cdots + l_{2k}F_k + e_2$$
$$\vdots$$
$$X_p = l_{p1}F_1 + l_{p2}F_2 + \cdots + l_{pk}F_k + e_k$$

Where $p = 1 \ldots 5$; $F_1, F_2, \ldots, F_k$ are common factors; $e_1, e_2, \ldots, e_p$ are unique factors, and l_{jh} is the load of each factor *h* on variable *j*; i.e., the factor loading or variable saturation *j* on factor *h*. Consequently, each observable variable *p* is a linear combination of the common factors *k* to all variables (*k*<*p*) and of a single factor for each variable, thus we obtain a factorial model with the following matrix form:

$$\begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_p \end{bmatrix} = \begin{bmatrix} l_{11} & l_{12} & \cdots & l_{1k} \\ l_{21} & l_{22} & & l_{2k} \\ \vdots & & \ddots & \vdots \\ l_{p1} & l_{p2} & \cdots & l_{pk} \end{bmatrix} \begin{bmatrix} F_1 \\ F_2 \\ \vdots \\ F_k \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_k \end{bmatrix}$$

which is equivalent to:

$$X = LF + e$$

Given that variables X are standardized variables, their covariance matrix is equal to the correlation matrix. Variance decomposition of the standardized variables can be expressed as:

$$V_j = 1 = l_{j1}^2 + l_{j2}^2 + \cdots + l_{jp}^2 + \omega_j^2$$

and if we also designate

$$h_j^2 = l_{j1}^2 + l_{j2}^2 + \cdots + l_{jp}^2$$

we have the variance decomposition for variable Xj as:

$$V_j = 1 = h_j^2 + \omega_j^2 \qquad j = 1 \ldots p$$

Thus, h_j^2 is part of the variance for variable X_j due to the common factors referred to as commonality. In the case of specificity, ω_j^2 is the part of the variance for variable X_j due to the unique factors and the correlation for each original variable is given according to the coefficients of the common factors:

$$\rho_{hj} = l_{h1}l_{j1} + l_{h2}l_{j2} + \cdots + l_{hp}^2 = \sum_{s=1}^{p} l_{hs}\, l_{js}$$

Obtaining the index was estimated based on the iterated principal factor method, which is a process that is part of the calculation of the sample correlation matrix;

$$R = \begin{bmatrix} 1 & r_{12} & \dots & r_{1p} \\ r_{21} & 1 & & r_{2p} \\ \vdots & & \ddots & \vdots \\ r_{p1} & r_{p2} & \dots & 1 \end{bmatrix}$$

Commonalities were estimated by calculating the regression of each variable over the remaining original variables, estimating the variable's commonality using the coefficient of determination obtained from the regression. The primary diagonal of the matrix *R* was replaced by the commonality estimate for each variable. Matrix *R* modified in this way was then referred to as the reduced correlation matrix R^*

$$R^* = \begin{bmatrix} \hat{h}_1^2 & r_{12} & \dots & r_{1p} \\ r_{21} & \hat{h}_2^2 & & r_{2p} \\ \vdots & & \ddots & \vdots \\ r_{p1} & r_{p2} & \dots & \hat{h}_p^2 \end{bmatrix} = R - \hat{\Omega}$$

The eigenvalues and eigenvectors associated with matrix R^* were calculated, and based on these we calculated the estimated factor loading $\hat{h}_{jh}$. k factors were determined via principal component analysis with the retained k factors

$$\hat{h}_j^2 = \hat{l}_{j1}^2 + \hat{l}_{j2}^2 + \dots + \hat{l}_{jp}^2$$

and the specificity or part of the variance due to the unique factor was estimated as:

$$\hat{\omega}_j^2 = 1 - \hat{h}_j^2 \qquad j = 1 \dots p$$

The results of the estimate were rotated to maximize the solution based on the Varimax method and the scores were estimated based on the regression method, starting from considering the regression of factor $\hat{h}_{jh}$ over variables X.

$$\hat{F}_i = \hat{\beta}_1 X_1 + \dots + \hat{\beta}_p X_p = \hat{\beta}_i X$$

Where it was checked that $\widehat{F}_i$ given $E\left[(F_i - \widehat{F}_i)^2\right]$ is minimal and the coefficients $\hat{\beta}$ are obtained from the ratio $\widehat{\beta}_i = R^{-1}\delta_i$ with the column vector of the correlations being between factor F_i and variables X. Estimating F_i using $\widehat{F}_i$ the following is obtained:

$$\hat{F}_i = \delta_i' R^{-1} X$$

and considering common factors m we obtain:

$$\hat{f}_i = S R^{-1} x$$

Where S=LT is the matrix of the factorial structure, in the case of orthogonal factors S=L so we have:

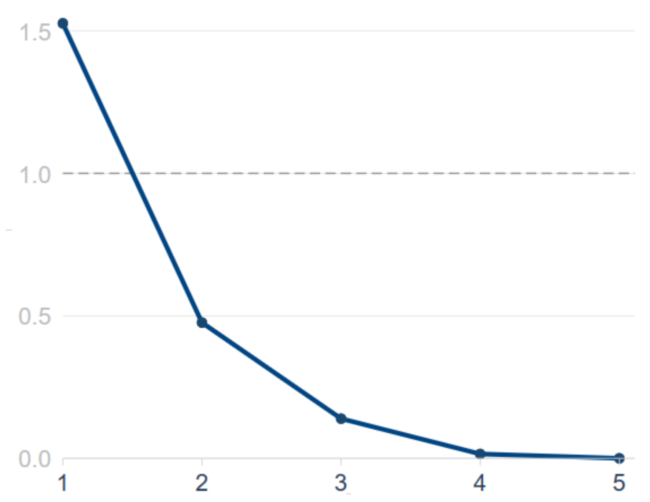
$$\hat{f}_i = S \cdot R^{-1} x$$

In summary, index estimation was carried out in five phases:

1. Estimation of a matrix capable of showing the joint variability of all variables
2. Extraction of the optimum number of factors based on the iterated principal factor method
3. Varimax rotation
4. Obtaining factor scores for each observation with which the index was built
5. Normalization of base-ten results

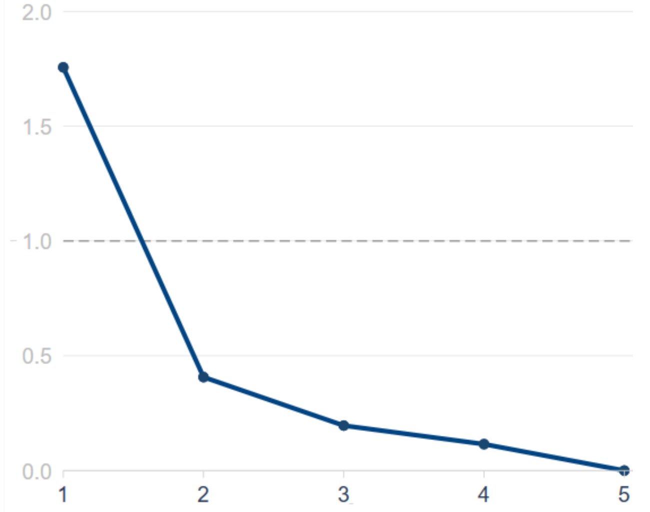
Once the estimates were carried out, the model retained 5 factors, however, given the results, only the first factor had an eigenvalue greater than 1, thus the index was estimated retaining only one factor.

Graph 7. **SCREE PLOT, NATIONAL MODEL**



Source: BBVA Research

Graph 8. **SCREE PLOT, URBAN MODEL**

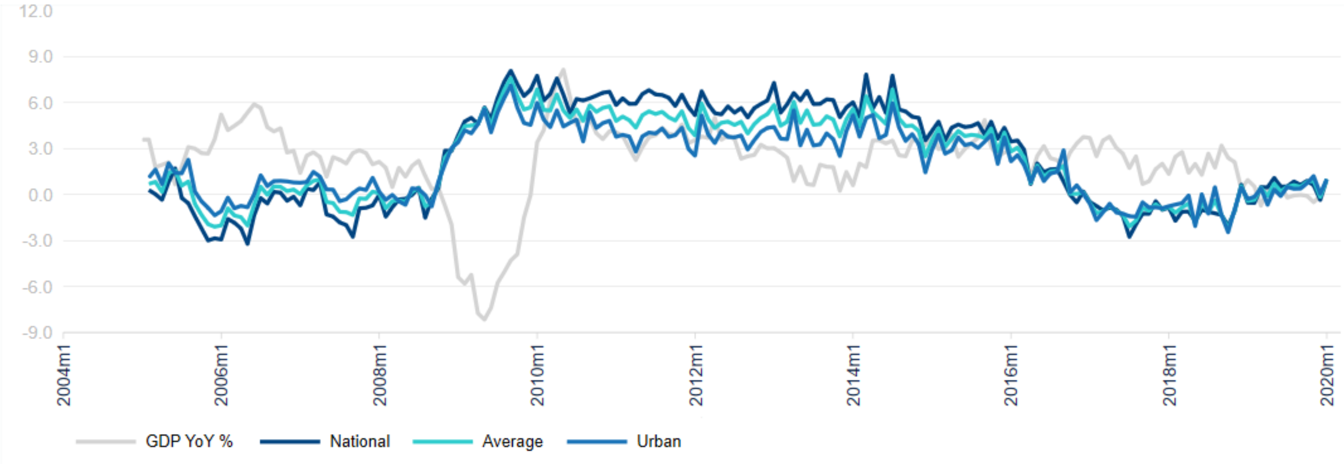


Source: BBVA Research

Stress and Performance Index for the Labor Market in Mexico (LM-SPI)

Based on the estimation of the normalized factor scores, the Stress and Performance Index for the Labor Market in Mexico was obtained at the national and urban levels, as well as their respective averages, the behavior of which is inverse to GDP growth throughout the series. Four relevant phases of LM-SPI behavior were identified, the first covering the period from 2005-1 to 2018-10 with economic growth that began to weaken gradually, becoming much more apparent from 2016 onward and with high LM-SPI variability, especially in urban areas.

Graph 9. **LABOR MARKET STRESS AND PERFORMANCE INDEX** (LM-SPI)



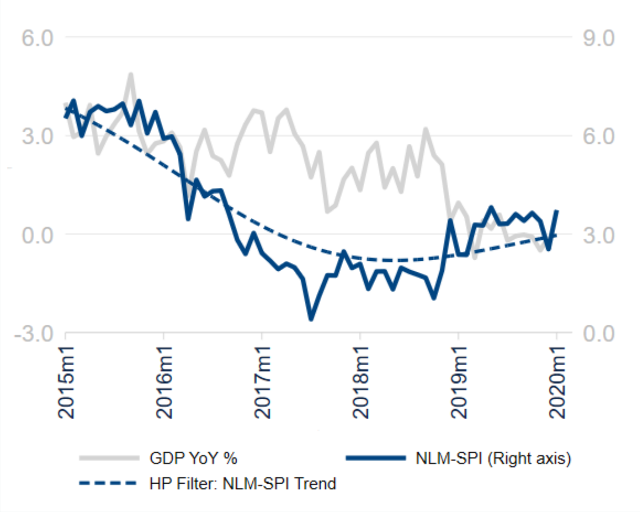
Source: BBVA Research and INEGI

The second phase was from 2008-11 to 2014-2, a period that includes the global economic crisis. At this stage, the LM-SPI increased rapidly and practically simultaneously with the fall in GDP, at one point tripling its levels; neither the unemployment rate nor IMSS employment reflected this increase in labor market stresses. After slowing the decline, GDP experienced a quick recovery with annual growth rates of more than 5%; however, this growth was not sustainable and again began a long process of an economic slowdown. In this context, the LM-SPI was consistent with short-term variations in GDP, but not with structural variations, i.e., despite high GDP growth in the months following the crisis, the LM-SPI did not recover and, on the contrary, remained high until the end of this period.

The third phase identified was the period between 2014-3 to 2018-8. At the beginning of this period, economic recovery began to have positive effects on the labor market, and the LM-SPI started to a sustained and consistent decline, mainly at the national level, maintaining consistency in the fluctuations of the economy in the short term.

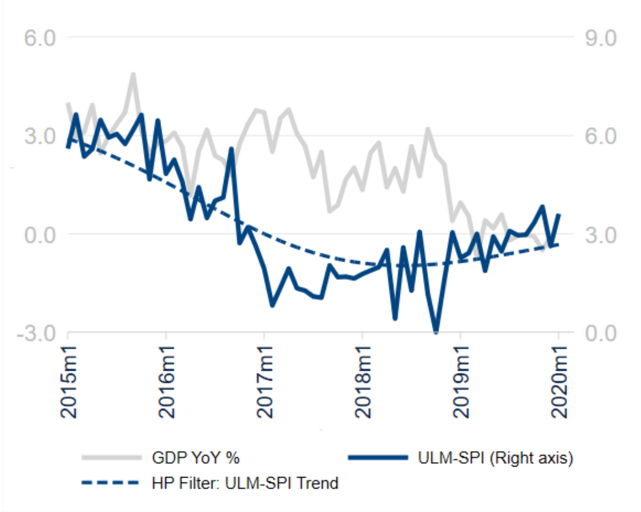
In the fourth phase, corresponding to the period between 2018-9 to 2019-09, the economy had begun a major slowdown phase, worsening labor market access conditions and generating an LM-SPI with an increasing trend. The negative effects initially occurred in urban areas, and subsequently in national areas.

Graph 10. **GDP AND NLM-SPI (National)**



Source: BBVA Research and INEGI
HP filter λ = 14400

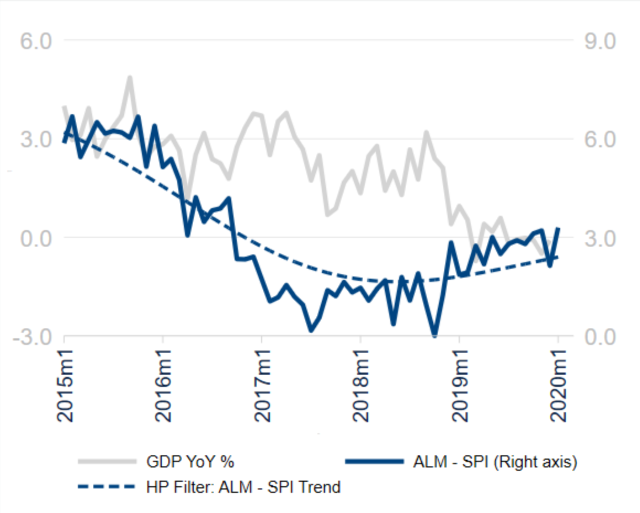
Graph 11. **GDP AND ULM-SPI (Urban)**



Source: BBVA Research and INEGI
HP filter λ = 14400

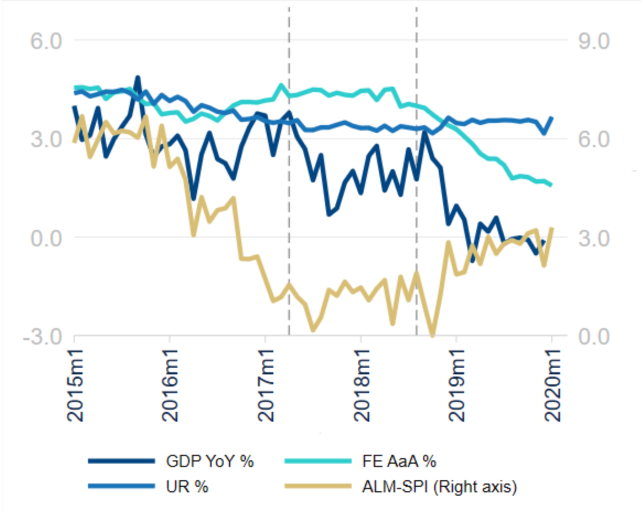
One of the advantages of the LM-SPI is that, by combining the different labor market indicators into a single index, different effects can be captured simultaneously and in a summarized way; the above can be seen when analyzing the formalization period, which is indicated on graphs with vertical parallel dotted lines. During this period, the IMSS Formal Employment indicator demonstrated virtually constant behavior, while the LM-SPI, which contains this information and the other rates, reflected other fluctuations in the market that were not visible using the indicators on their own.

Graph 12. **GDP AND ALM-SPI (Average)**



Source: BBVA Research and INEGI
HP filter λ = 14400

Graph 13. **GDP, FORMAL EMPLOYMENT, UNEMPLOYMENT RATE AND ALM-SPI**



Source: BBVA Research, IMSS and INEGI

Finally, an ARIMA model was estimated for illustrative purposes only, where the dependent variables were the average and national LM-SPI indices, and only the GDP and it's 3- and 6-period time lags were included as the independent variable. The results of the models adjusted and validated based on compliance with the assumptions reflect a negative correlation with GDP in the short term, where the lagged variable has no statistical significance. This confirms that the index responds to short-term fluctuations in GDP.

Table 2. **ESTIMATION OF ARIMA MODEL PARAMETERS**

Variable	ALM-SPI: Average	NLM-SPI: National
D.(LOG(GDP))	-10.660** [6.091]	-8.798** [5.27]
D.L3.(LOG(GDP))	8.762 [6.606]	6.278 [6.154]
D.L6.(LOG(GDP))	6.731 [6.111]	1.858 [5.818]
AR(1)	-0.993*** [0.006]	-0.994*** [0.005]
MA(1)	-0.334*** [0.069]	-0.3186*** [0.069]
Constant	0.556*** [0.060]	0.471*** [0.045]
R^2 Durbin-Watson stat	0.925 1.983	0.941 2.024

Source: BBVA Research
D - First difference operator
L - Lag operator
Standard error in [ ]
*** 1% significance level; ** 5% significance level; * 10% significance level;

Another element worth mentioning is the coefficient size, which much more relevant than the additional components. It should be emphasized that this estimate does not take into account other variables that are also important in the labor market; however, it does allow us to validate that there is a statistically significant relationship between the indices and economic dynamics.

Conclusions

The Stress and Performance Index for the Labor Market is a measure that enables consistent capturing of short-term movements as well as the relevant long-term changes in the labor market. The combined effects of the variables as a whole provide us with a better idea of the effects of labor dynamics on the country. At the urban level, the index is able to more quickly reflect changes in the labor market, which are then reflected at the national level.

The analysis of the labor market must be carried out in conjunction with a series of complementary indicators; in this sense, the LM-SPI makes a contribution that complements these indicators, and that can show aggregate changes in the labor market in a simple and clear way.

The LM-SPI is an indicator from BBVA Research that complements the country's macroeconomic environment analysis and will be presented on a monthly basis in employment bulletins or when there is sufficient information to estimate it.

References

Bureau of Statistics, O. (2003). International training compendium on labor statistics. Switzerland: International Labor Organization.

Cervantes A., D. (2017). In*estabilidad Laboral en México: Análisis de trayectorias, movilidad e impacto del tipo de contratación*, 2005-2015. Mexico: Tesis-UNAM.

Hair Jr., J. F., Anderson, R. E., Tatham, R. L., & Black, W. C. (1999). *Análisis multivariante*. Spain: Pearson.

Heath, J. (2012). *Lo que indican los indicadores: cómo utilizar la información estadística para entender la realidad económica de México*. Mexico: National Institute of Statistics and Geography of Mexico (INEGI).

Islas Camargo, A., & Cortez, W. W. (2013). *Relaciones dinámicas del producto y el empleo en México: una evaluación de sus componentes permanentes y transitorios*. ECLAC publication, 167-182.

Lawrence C., H. (2009). Statistics with STATA. Canada: CENGAGE Learning.

Poghosyan, A., Harutyunyan, A., & Grigoryan, N. (2017). Compression for Time Series Databases using Independent and Principal Component Analysis. IEEE International Conference on Autonomic Computing (ICAC), 279–284.

Appendix

Table 3. **ITERATED PRINCIPAL FACTOR MODELS FOR THE NATIONAL LM-SPI**

Estimation method: IPF (Iterated principal factor)

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	1.52661	1.05049	0.7079	0.7079
Factor 2	0.47612		0.2208	0.9287

Estimation method: IPF (Iterated principal factor)
Rotation: orthogonal varimax
Retained factors = 1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	1.24370	0.49544	0.5767	0.5767
Factor 2	0.74826	0.60739	0.3470	0.9237

Source: BBVA Research

Table 4. **ITERATED PRINCIPAL FACTOR MODELS FOR THE URBAN LM-SPI**

Estimation method: IPF (Iterated principal factor)

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	1.75643	1.34947	0.7100	0.7100
Factor 2	0.40696	0.21121	0.1645	0.8745

Estimation method: IPF (Iterated principal factor)
Rotation: orthogonal varimax
Retained factors = 1

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor 1	1.60617	1.10039	0.6493	0.6493
Factor 2	0.50578	0.27376	0.2045	0.8537

Source: BBVA Research