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Article

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Not everyone is engaged: an innovative approach to measure engagement levels on the labor market

Abstract

In this paper, we analyze the Individuals' level of engagement on the labor market and the engagement heterogeneity across individuals in matters of labor market outcomes and the effectiveness of policy interventions. Emerging economies with highly segmented and distorted labor markets typically exhibit strong heterogeneity in labor market engagement. This paper develops an innovative index that measures individuals' labor market engagement across three dimensions (preferences, intensity, and barriers) and across three labor market categories (employed, unemployed, and out-of-labor force) based on a recent special labor market survey in the Kingdom of Saudi Arabia (KSA). Clustering individuals with similar engagement levels permit more effective targeting of labor market interventions. Findings confirm the strong heterogeneity of labor market engagement in the KSA and the index's usefulness in the construction of differentiated policies across these clusters.

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1 Introduction

The traditional measures of labor market categories – employed, unemployed, and out-of-labor-force (OLF) – and related labor market outcomes may not divulge all the required information to labor market agents if the level of labor market engagement between individuals is highly heterogeneous within and across the different outcome categories. For example, an employee's level of engagement matters to firms as it affects their productivity; hence firms will aim to have highly motivated employees who face no barriers in the performance of their tasks. As a second example, labor market engagement also matters for employment offices and policy makers. Not all unemployed individuals display the same interest in searching for jobs, so understanding their willingness to participate in the labor market can help policy makers design and select the right interventions to promote engaged job seekers and to move capable individuals out of their OLF status.

Countries with highly segmented and distorted labor markets usually exhibit heterogeneity in labor market engagement, which may lead to poor labor market and productivity outcomes. Hence, without knowing the level of engagement in its different dimensions, key market dynamics may not be grasped, and labor market policies will be inefficient or difficult to implement.

How should we define, measure, and compare the level of labor market engagement of individuals with different labor market exposures and experiences? In each of the standard labor market groups (employed, unemployed, and OLF), heterogeneity emerges as a reflection of the special social, economic, and cultural norms taking place in a region at a specific time. However, differences in labor market engagement are typically ignored in conventional (neoclassic) labor market considerations where, for example, conditional on a given wage, individuals are willing to work, or not, at a standard effort level. Whereas these assumptions are reasonable for mature market economies, they appear to be unreliable for designing labor market interventions for countries with labor markets highly segmented and distorted across gender, age, education, and other socioeconomic characteristics.

Beyond the neoclassical approach, the current literature is tackling very specific issues of engagement against the background of developed economies. In particular, the current literature focuses on three types of labor market engagement. The first focus, illustrated in the work of Fernandez et al. (2016) and Immervoll and Scarpetta (2012), is dedicated to the existence of barriers (both technical and social) that deter the engagement of people in the market and suggests some methodologies to identify the key barriers and generate policies to reduce them. The second focus, exemplified by authors such as Gauthier et al. (2016) and Eugster et al. (2017), is dedicated to people's attitudes toward work. In particular, these authors highlight how the interaction between culture, gender, and socioeconomic level can change how people perceive work and, consequently, their willingness to be part of the labor force. The final focus occurs in the work of authors such as Harrison et al. (2006) and Dunn et al. (2014), who study some of the characteristics that define the job search effort of unemployed people as well as the commitment that workers can have to their jobs. In this literature, the central issue is to identify heterogeneity in the level of energy that individuals employ to become part of or to stay in the labor force. Whereas all these papers deal with key issues regarding labor engagement, two key facts highlight the gap in the literature on this topic. On one hand, and to the best knowledge

of the authors, no unified way has been found to integrate the previous elements (work barriers, preferences, and effort to engage in labor markets) into a single conceptual framework conducive to practical policy analyses. On the other hand, works such as that of Fernandez et al. (2016) propose methodologies that depend on specific data sources that are unlikely to be available in the majority of countries. Hence, a conceptual gap exists related to the framework in which the different engagement elements can be studied, and an empirical gap on how to calculate these elements from the already standardized surveys. As explained before, the countries where heterogeneity is a central issue are those with less mature markets and where resources for specialized studies are not readily available. Hence, the framework must be flexible enough to be implemented using the existing data collection mechanisms such as labor force surveys.

To fill the conceptual and empirical gaps, this paper develops and estimates an engagement index called the Relative Engagement Labor Index (RELI) that can be executed using standardized surveys. Building on the previous literature, the paper suggests three dimensions to conceptualize into the same envelope the different notions of labor market engagement: the extent of individuals' preferences to be engaged; the intensity of the effort they undertake to be engaged; and the constraints they face to be engaged. A principal component methodology is adopted to construct the index and estimate the level of engagement using labor market survey data. Cluster analysis is then undertaken to profile subpopulations according to engagement levels to target interventions to emerging clusters and apply the findings in the labor market policies.

The purpose of RELI is therefore fourfold:

1. To establish the scope, depth, and heterogeneity of labor market engagement for national labor market groups by socioeconomic characteristics. This should inform policy makers on the size of the problem.
2. To use these disaggregated results to design and direct policy interventions toward groups with low engagement levels. Successful profiling of engagement-distant groups is expected to emerge as an operational and effective approach.
3. To detect relevant differences in aggregate results across all labor market groups by socioeconomic characteristics, which may offer guidance about policy gaps and intervention opportunities.
4. To suggest a set of questions that can be used to evaluate the effectiveness of interventions applied between different measurement periods.

To the best of the authors' knowledge, few attempts have been made to move well beyond traditional labor market categories and to exploit household data and ad hoc surveys for some measure of engagement. The International Labour Organization (ILO) and the World Bank use ADePT software to translate household survey data into ready-to-use analytical labor market tables (Pietschmann et al., 2016). In the United States, a labor market engagement index aggregates levels of employment, labor force participation, and education levels to measure geographic differences in engagement across countries.[1] Last but not least, measures of labor intensity (occupation, days, and hours worked) are also used to explain the differences in body mass index (BMI) and to explore their causal link.

1 https://data.world/hud/labor-market-engagement-index.

The methodology of index construction described in this paper – the principal component analysis (PCA) – is widespread and well developed. Many examples exist in the literature of PCA applications in economics; a few of them are cited in this paper. Cordova (2008), for example, uses PCA to construct a relative wealth index based on household assets for 21 Latin American and Caribbean countries. Fuchs et al. (2018) use PCA to reduce the dimensionality of demographic variables when forecasting labor participation. Filmer and Pritchett (2001) use PCA to construct a linear wealth index from asset ownership indicators for Indonesia, Pakistan, and Nepal and correlate the index with school enrollment. Huh and Park (2018) use PCA to develop a composite index to measure the degree of regional integration in Asia. Drafor (2017) uses PCA to reduce the number of variables in the Ghana Living Standards Survey to construct a spatial index, analyzing the spatial disparity between rural and urban areas.

Finally, to illustrate the use of the methodology, this paper uses labor market surveys from the Kingdom of Saudi Arabia (KSA) that were developed to gain a better understanding of the country's labor market status, dynamics, and outcomes. The KSA labor market is a representative example of a population with a high degree of heterogeneity in its engagement as it is segmented by at least three dimensions: (i) between KSA nationals and foreign workers; (ii) between the public sector, where most KSA nationals work, and the private sector, which is dominated by foreign workers; and (iii) between men and women. This paper deals with the two latter dimensions. Furthermore, both the open demand-driven admission scheme of foreign workers and the way national oil wealth is redistributed in the KSA create major distortions in the labor market (Bodor and Holzmann, 2015). These distortions may have an impact on the engagement levels of KSA nationals. Being able to quantify the heterogeneity of labor market engagement in the KSA is central to the design and implementation of better policy interventions. For the sake of clarity, the current paper focuses only on KSA national workers; however, another natural extension of the framework developed in this paper is the study of foreign workers.

The paper is organized as follows. Section 2 presents the data and methodology used to construct the index. Section 3 presents the results based on the application of the index to the KSA data. Section 4 discusses the potential policy applications of these findings. Section 5 concludes. A comprehensive annex details some of the results (with more details on request and online).

2 Methodology

2.1 Data

Data from a comprehensive labor market survey of KSA nationals were used to construct the index. The survey was conducted between November 2015 and January 2016. A total of 4,939 KSA nationals were sampled via a tightly controlled quota sample whereby interviewers had to recruit respondents to meet a set of criteria on key respondent characteristics. These quotas were derived for economic activity status (OLF, unemployed, and employed), age group, and gender, all categorized by province. Out of the total number of individuals 3,954 were not studying, had no disabilities, and were in the age range 18–64, making them adequate for the study. Within this group, the distribution of the male sample was 282 OLF, 277 unemployed,

and 1,699 employed; the distribution of the female sample was 564 OLF, 261 unemployed, and 871 employed.

Questions in the survey included information on the characteristics and employment status of Saudi nationals, attitudes to work and barriers for women's employment and participation in the labor market, job characteristics for those employed, the economic history of those interviewed dating back to the last 10 years, job search intentions and efforts for both employed and unemployed Saudis, income information, and views on certain interventions being implemented in the KSA. However, some of these questions were not answered by the full sample of individuals. The final distribution of the sample was 274 OLF, 216 unemployed, and 1,420 employed for men; and 118 OLF, 180 unemployed, and 646 employed for women.

2.2 Index construction

2.2.1 Index composition

Engagement is defined as a combination of three different dimensions that jointly determine the level of interaction of the individual with the labor market and allow measurable comparisons between individuals. These dimensions are (i) barriers for working (social and technical); (ii) individuals' preferences toward work; and (iii) intensity of work or job search. Although preferences and intensity both highlight individuals' willingness to work, preferences focus on the breadth of individuals' willingness to work (i.e., attitudes toward characteristics of a job), while intensity focuses on the depth (how much of each activity a person is willing to do).

The index is calculated for six groups of the population: (i) OLF men; (ii) OLF women; (iii) unemployed men; (iv) unemployed women; (v) employed men; and (vi) employed women. The paper identifies the six groups by considering variables that have strong social implications regarding the way individuals behave, namely, gender and work status. Women and men face structurally and historically different social realities, so pooling them together may bias identification of the vulnerability of the population in each group. The types of interactions of each of the three work status categories with the labor market are also systematically different and denote different levels of motivation and capacity to participate in the market. It is important to highlight that these groups are not unique. Depending on the country-specific situation, other grouping factors can also be relevant (e.g., regional idiosyncrasies, ethnicities, or creed). However, as the purpose of this section is to illustrate the methodology rather than the specific situation in Saudi Arabia, only the most general categories were chosen.

2.2.2 Selection of variables

The three dimensions (barriers, preferences, and intensity) are inherently unobservable, and thus, it is not possible to extract them from a single question. For that reason, their measurement relies on the identification of several questions associated with each dimension. However, no unique set of questions accurately defines each dimension. Engagement is a social and contextualized concept. Thus, some variables that are central in some countries might prove to be irrelevant in others. For example, in Saudi Arabia, women face social barriers that may not exist in other countries. For these reasons, the following procedure is intended to guide the reader through the selection process rather than providing a definitive set of variables for the index.

First, economic experts with local knowledge were consulted to identify all the possible variables that can be associated with each dimension. Once the preselection was done, two additional criteria were used to filter the variables. The first criterion pertains to the identification of variables that have variance. For example, the labor force survey of KSA nationals asks two questions regarding the type of works that individuals will find acceptable or unacceptable. Originally, these questions seem relevant for the identification of preferences. However, all OLF individuals answer these questions in the same way. Thus, the lack of variance makes the questions uninformative. The second criterion is with regard to the identification of highly correlated variables. By construction, all selected variables are expected to be related as all of them are manifestations of the underlying dimension. However, given the way the questions are asked in the survey, two questions can have the same information. Thus, by examining the correlation structure of the questions, those cases that provide identical information were removed to avoid giving larger weights to single elements. One example of this point is the question: "Has anybody influenced your decision not to do paid work?" and the other question "Who has influenced your decision?" Both questions are highly relevant for the identification of social barriers, but due to the response pattern, both had the same information. Hence, only one of the variables was kept. The final set of variables selected is described in the annex.

2.2.3 **Application of PCA**

The selected variables are first transformed so that positive values are linked with higher levels of engagement. PCA is then used to extract the common information of these variables (Johnson and Wichern, 2007). The applications of PCA traditionally use Pearson correlations to identify the common information between variables. Examples of their applications can be found in Filmer and Pritchett (2001) and Vyas and Kumaranayake (2006). Yet when the variables are ordinal, Pearson correlations are not ideal. Thus, this exercise also conducted PCA analysis based on Spearman's Rank correlations[2] as a robustness check.[3] As Table 1 illustrates for OLF women, the results of the first principal component under both methodologies were qualitatively similar. In the case of Saudi Arabia, this similarity between the index was common among the different groups and clusters. However, as discussed in later sections, the Pearson correlation facilitates the evaluation of public policies. Therefore, this paper focuses on the Pearson correlations methodology when presenting findings in Section 3.

Once PCA weights are calculated for each dimension within a group, the formula to calculate the score of a specific individual becomes

$$Dimension(j) = \frac{\sum w_i \frac{\left(x_{ij} - \overline{x_i}\right)}{s_i}}{s_{dimension}},$$

2 There are alternatives to Spearman's Rank correlation matrix. For example, Howe et al. (2008) offered a solution calculated with polychoric correlations. Whereas this methodology is mentioned, it was not considered for two reasons: (i) PCA scores obtained from polychoric correlations cannot be reconstructed for individuals who were not in the baseline. Hence, it would be very difficult to design policy evaluations using it and (ii) the strong similarity of Spearman and Pearson results suggests that the relevant information is captured using these two methods, which are easy to extend for policy evaluation scenarios.

3 The current results were calculated using the statistical software R. It was chosen due to its flexible format, which allowed PCA analysis with correlation matrices different from those using Pearson correlations.

Table 1 PCA scores for OLF women

	Variable	Weight	
Preferences	**Correlation**	**Pearson**	**Spearman**
1	reasons_not_working	0.58	0.59
2	women_mixing_thoughts	0.4	0.39
3	women_work_attitude	0.43	0.43
4	work_attitude	0.56	0.56

Source: Authors' elaboration.

where *Dimension* (*j*) is the value of the dimension of individual *j*; x_{ij} is the value of variable *i* for individual *j*; $\overline{x_i}$ and s_i are the mean and standard deviation of this variable in the group, respectively; w_i is the weight of that variable in the dimension; and $s_{dimension}$ is the overall standard deviation of the dimension. This last division is important as it guarantees that all the dimensions are standardized to have a mean zero and a variance one.

2.2.4 **Aggregation**

The final step of the process is the construction of a unique index that synthesizes the engagement of an individual to the labor market. A priori, all dimensions are equally important to understand the engagement. Thus, an intuitive aggregation mechanism is to give each dimension the same weight and add them together.

$$\text{RELI} = \frac{1}{3} Barriers + \frac{1}{3} Intensity + \frac{1}{3} Preferences$$

Nevertheless, a different context might need a modified weighting scheme, and therefore researchers and policy makers might prefer to reconfigure these weights. For example, in countries where people are in general willing to work, but the main problem is their skill level, it would be relevant to take some weight from the preferences, as in general people want to work, and add this weight to the barriers, where most of the dynamics are taking place. In the case of Saudi Arabia, the index was illustrated via equal weights.

With the construction of RELI and its dimensions, the engagement of an individual relative to the average of his/her group is estimated. Individuals who are above the average in each dimension will have higher levels of engagement than individuals below the average.

2.2.5 **Aggregation across all six groups**

Policy makers may be interested in aggregating the indices across all individuals independent of the six groups (unemployed, employed, and OLF, by women and men). It is possible to do so even though the groups were constructed with different variables and weights. This is because each dimension was standardized when the index was constructed. To illustrate this point, for each age range (i.e., 18–24, 25–34, 35–44, 45–54, and 55–64), the average values of the preference dimension are calculated. Figure 1 presents the results. In this figure, the preference index for individuals aged 18–24 is concentrated around 0.3. It is important to notice that each group has a different standard; e.g., for unemployed groups, higher preferences suggest more flexibility looking for a job, while for employed groups, higher preferences suggest working shifts

and extra hours. Nevertheless, independent of the group, individuals of the youngest cohort tend to have a positive preference toward work that is 0.3 standard deviations higher than the average individual of the group, and this commonality is meaningful for policy design. Furthermore, this exercise shows that as age increases, the preference index is systematically lower. By replicating this procedure for different policy variables (e.g., education level and province), it is possible to characterize how these variables are associated with each dimension and RELI.

2.3 Extensions to the index

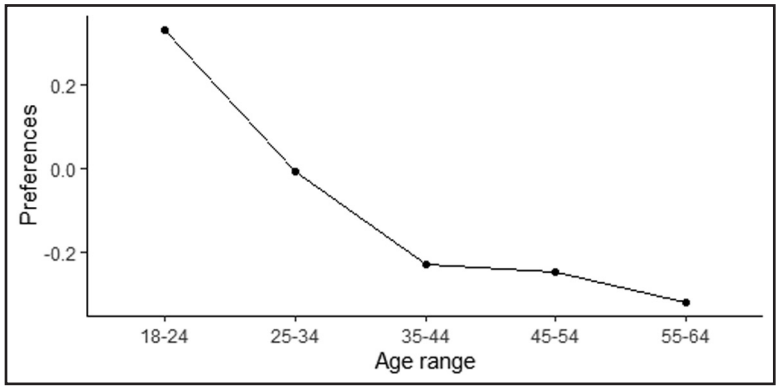
2.3.1 Identification of clusters

One of the index's main applications is that it can be used to profile individuals. However, the continuous calculation of individuals' scores may be costly and subject to data noise. In contrast, once clusters are defined, it is possible to associate observable variables to an individual belonging to a specific cluster. In this way, policy makers can identify target populations promptly.

For the illustration of Saudi Arabia, clusters with shared characteristics are identified using Ward's method hierarchical clustering over the three dimensions (Rokach and Maimon, 2005). The method is carried out at the dimension level rather than in aggregate as it captures more information about the particularities of each cluster. Figure 2 presents the case of OLF women.

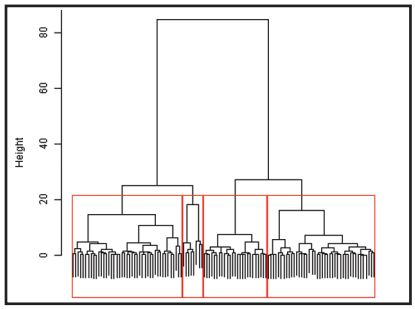
Although no consensus exists about the best way to determine the number of clusters, too many clusters may not be useful to policy makers because the policy may end up being

Figure 1 Preferences by age – mean comparison.



Source: Authors' elaboration.

Figure 2 Hierarchical clustering for OLF women.



Source: Authors' elaboration.

case-specific. On the other hand, having no clusters creates issues because policies will treat individuals with heterogeneous conditions equally. Due to these considerations, and based on the previous dendrogram, for public policy in the KSA, this paper recommends four clusters. Following the cluster identification, it is possible to measure the average index value of each dimension (and overall index) in each cluster.

2.3.2 **Construction of the index for out-of-sample individuals**

The inclusion of individuals who were not part of the original sample (e.g., newly registered jobseekers) is important to policy makers. For that reason, the previous process was designed to facilitate computing the index value of a new individual. For this purpose, recall that the formula used to calculate the dimension value is:

$$Dimension(j) = \frac{\sum w_i \frac{\left(x_{ij} - \overline{x_i}\right)}{s_i}}{s_{dimension}}$$

Thus, the score of new individuals can be computed by using the values of w_i, $\overline{x_i}$, s_i, and $s_{dimension}$ from the sample, and using the x_{ij} of the incoming individual.

A particular application of the previous calculation is used to track policy changes across the years. For illustration purposes, the methodology is described for the dimension of the barrier, but it can be applied to other dimensions and the aggregate index.

Let x_{ijt} be the value of the variable i for an individual j during the period t, where $\overline{x_{it}}$ and s_{it} are the respective mean and standard deviation of this variable in time t. In that same way, w_{it} is the PCA weight of variable i constructed with the information of year t and $s_{dimension,t}$ its corresponding standard deviation. Finally, let $\mathbb{F}$ be the subsample of the size f of individuals who will be tracked for two periods, and $Barriers_t(\mathbb{F})$ the average barrier value of that group.

In that case,

$$Barriers_t(\mathbb{F}) = \frac{\sum_{j\in\mathbb{F}}\left[\frac{\sum w_i \frac{\left(x_{ijt} - \overline{x_{it}}\right)}{s_{it}}}{s_{barriers,t}}\right]}{f} = \frac{\sum w_{it}\frac{\left(\sum_{j\in\mathbb{F}}\frac{\left[x_{ijt}\right]}{f} - \overline{x_{it}}\right)}{s_{it}}}{s_{barriers,t}} = \frac{\sum w_{it}\frac{\left(\overline{x_{it}(\mathbb{F})} - \overline{x_{it}}\right)}{s_{it}}}{s_{barriers,t}}$$

where $\overline{x_{it}(\mathbb{F})}$ stands for the average value of the variable i for an individual of the group $\mathbb{F}$.

The evolution of the group index is then represented by:

$$Barriers_{t+1}(\mathbb{F}) - Barriers_t(\mathbb{F}) = \frac{\sum w_{it}\frac{\left(\overline{x_{it+1}(\mathbb{F})} - \overline{x_{it}}\right)}{s_{it}}}{s_{barriers,t}} - \frac{\sum w_{it}\frac{\left(\overline{x_{it}(\mathbb{F})} - \overline{x_{it}}\right)}{s_{it}}}{s_{barriers,t}} = \sum w_{it}\frac{\left(\overline{x_{it+1}(\mathbb{F})} - \overline{x_{it}(\mathbb{F})}\right)}{s_{it}s_{barriers,t}}$$

By using this formula, policy makers can thus measure changes in engagement between two periods of time. Under that same logic, the methodology can also include situations with both a control and a treatment group. In that case, policy makers can use the parameters of the control group to compare the evolution of the treatment.

3 Results in the case of Saudi Arabia

3.1 Relative Engagement Labor Index

To exemplify how RELI can be used to determine how engagement levels differ by individuals' characteristics, this paper presents results by education and sector of employment for the six group indices, using data on the Saudi labor market.

Overall, after aggregating the three dimensions of the index, the results show that unemployed men and women with tertiary education have the highest engagement levels. For employed individuals, the highest engagement is manifested in people with vocational studies (0.69 standard deviations for women and 0.71 standard deviations for men). For OLF individuals, results differ by gender. Women who have undertaken vocational studies have the highest engagement levels, while this is true for men with a bachelor's degree.

Disaggregating by dimension, having a secondary degree or below lowers one's barriers relative to having a higher degree systematically across groups. The comparison between vocational education and a bachelor's degree is less clear. For women, vocational education reduces barriers more than a bachelor's degree. The opposite holds true for men. This difference in signs suggests jobs that are available for women require technical skills, while men's vacancies demand higher education.

On the other hand, the relationship between education and intensity levels depends on individuals' working status. For employed individuals, the lowest intensity is in the group with the highest education (−0.17 standard deviations for women and −0.21 standard deviations for men), while the highest intensity is obtained by people with vocational education (0.24 standard deviations for women and 0.33 standard deviations for men). This difference can be a consequence of the KSA's strong public sector, which hires bachelor's degree holders but does not incentivize higher work effort. For unemployed individuals, the opposite tendency occurs. In this case, the lowest intensity is in the group with the lowest education (−0.67 standard deviations for women and −0.17 standard deviations for men), while the highest intensity is obtained by people with the highest education level (0.73 standard deviations for women and 0.46 standard deviations for men). These numbers also highlight that these differences are stronger for women. One possible explanation is that educated people who are willing to work have a better knowledge of how to apply for jobs and therefore apply more often.

The relationship between educational and preference levels also depends on individuals' working status. The highest preferences for unemployed men and women are those with vocational education. Women's and men's preferences, respectively, are 0.68 and 0.47 standard deviations above the group average. On the other hand, employed women and men with tertiary education have lower preferences (0.31 standard deviations below the average for women and 0.14 standard deviations for men).

Finally, public sector workers have fewer barriers than private ones. For women, the difference between these two groups is 0.39 standard deviations, while for men the difference is 0.16 standard deviations. In contrast, public employees manifest lower intensity and preferences. For men, the differences are −0.17 and −0.36 standard deviations, respectively, while for women they are −0.35 and −0.78 standard deviations. This implies that people in the private sector have a more positive attitude toward work and may work more hours and exert more

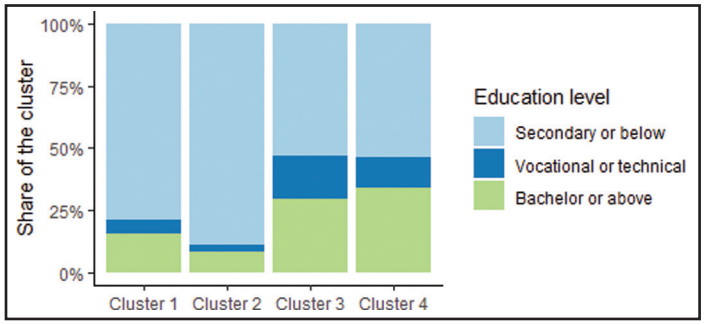
effort. Due to the strong effect on preferences and intensity, the overall effect of engagement is lower for public employees.

3.2 **Cluster analysis**

Individuals belonging to each of the six groups were divided into four clusters based on their preferences, intensity, and barriers. These clusters were ordered such that individuals in cluster 1 had the lowest RELI average, while those in cluster 4 had the highest one.

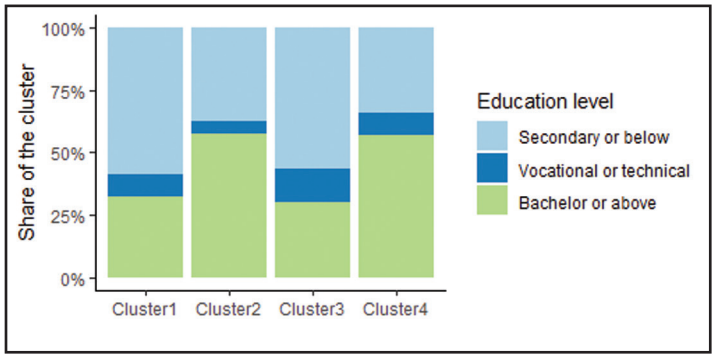
Figures 3–8 display the results of these exercises and show that the four clusters in each of the six groups have very different socioeconomic, demographic, and behavioral characteristics. For example, clusters 3 and 4 show that the most engaged unemployed Saudis are also

Figure 3 Share of unemployed men by education level.



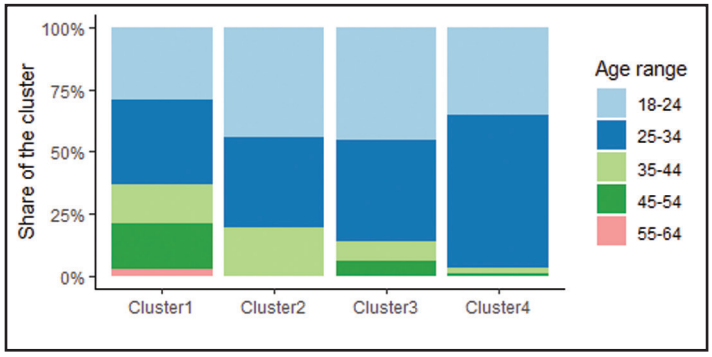
Source: Authors' elaboration.

Figure 4 Share of unemployed women by education level.



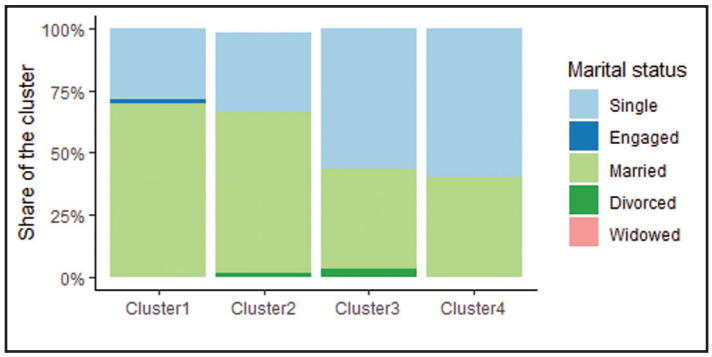
Source: Authors' elaboration.

Figure 5 Share of unemployed men by age range.



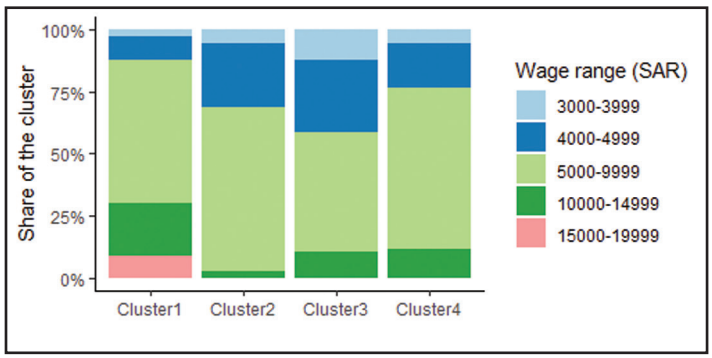
Source: Authors' elaboration.

Figure 6 Share of unemployed women by marital status.



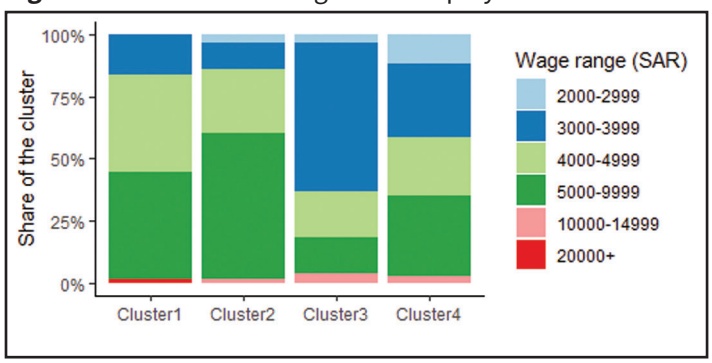
Source: Authors' elaboration.

Figure 7 Reservation wages – unemployed men.



Source: Authors' elaboration.

Figure 8 Reservation wages – unemployed women.



Source: Authors' elaboration.

the youngest. Within the unemployed men group, the least engaged tend to have the lowest educational levels; however, this is not the case for women, whose level of engagement is not correlated with their educational level but rather with marital status. The least engaged unemployed women have the highest share of married women.[4] While unemployed men have a similar reservation wage distribution, centered around 5,000–10,000 SAR/month, this is not the case for women. Unemployed women have systematically different reservation wages. Clusters 1 and 2 have very high reservation wages: the mode of the distribution is between

4 The four clusters for unemployed men have the following sample sizes: 38 in cluster 1, 36 in cluster 2, 61 in cluster 3, and 91 in cluster 4. The four clusters for unemployed women have the following sample sizes: 56 in cluster 1, 59 in cluster 2, 30 in cluster 3, and 35 in cluster 4.

5,000–10,000 SAR/month. This might be due to social barriers and preferences, which may lead women to only accept a job if the salary is high. Further, a significant share of cluster 2 has a bachelor's degree, which may be aimed at getting a public sector job that pays more, thereby influencing wage expectations. Cluster 3 has the lowest reservation wage, with a mode of 3,000–4,000 SAR/month. This is consistent with a young population that is willing to work and accept lower wages to join the labor market. Finally, cluster 4's reservation wages exhibit a bimodal distribution.

By construction, the three dimensions, which are based on variables from the data, determine the cluster's engagement level. Analyzing the differences between clusters in terms of the variables used to construct the engagement level[5] provides a more detailed story on what is affecting each of the four clusters' engagement levels, thereby assisting policy makers in proposing targeted interventions. For example, the unemployed men of cluster 1 are the hardest to place due to their preference and intensity levels. Cluster 1's preferences are 1.9 standard deviations below that of the average individual. This is driven by the fact that 90% of its members are not willing to relocate, more than 40% are not willing to work shifts, only 16% are willing to work more than 40 h/week, and they have the lowest share of individuals with the highest attitudes.[6] Cluster 1's intensity is also very low – 1.17 standard deviations below the group average. Around 76% of them updated their CV more than a year ago, 68% have applied at most to one job, and most of them spent barely any time searching, looking mainly at websites for jobs. On the other hand, cluster 2 of unemployed men has the lowest average on the barrier dimension, at 2.9 standard deviations below average. Due to their low education levels, lack of English, and young age, this cluster's members confront strong technical barriers when applying for jobs. For unemployed women, cluster 3's intensity is the lowest of all clusters (1.6 standard deviations below the average) even though they have high engagement regarding preferences and barriers. More than 80% have a positive attitude toward work. However, their main effort for job searching is looking through traditional advertisements and many do not apply for jobs.

Table 2 closes this section by presenting the average scores of each dimension and RELI across the different groups and clusters.

4 Policy applications

4.1 Profiling jobseekers

The findings from the cluster analyses disaggregated by the six population groups can be used to propose targeted interventions for each cluster. The paper focuses on the unemployed groups to demonstrate how RELI and clustering based on engagement levels can be an effective profiling procedure for Saudi jobseekers.

Table 3 summarizes the profiling intervention proposals for each of the four clusters based on the findings. The unemployed men and women in cluster 1 would benefit most from

5 A pivot table was constructed in Excel to conduct such analysis.

6 Individuals who have the highest attitudes are those who agreed or strongly agreed with all of the following six statements: Life without work is very boring; I believe self-reliance is the key to being successful; Working is an important part of who I am; I always look out for opportunities for improving my situation; I find a hard day's work very fulfilling; and I would rather be at home than go to work (negative value).

Table 2 Engagement levels of clusters

Labor Market Group	Preferences	Intensity	Barriers	RELI
OLF – Men				
Cluster 1	−0.25	−3.00	1.38	−1.86
Cluster 2	−1.84	0.38	−0.16	−1.62
Cluster 3	0.59	0.36	−0.97	−0.02
Cluster 4	0.66	0.36	0.15	1.18
OLF – Women				
Cluster 1	−0.59	−3.37	1.28	−2.68
Cluster 2	−1.51	−0.54	−0.07	−2.12
Cluster 3	1.05	0.12	−0.31	0.87
Cluster 4	1.02	1.80	0.22	3.04
Unemployed – Men				
Cluster 1	−1.91	0.27	−1.17	−2.80
Cluster 2	0.15	−2.87	0.49	−2.23
Cluster 3	1.03	0.80	−1.66	0.16
Cluster 4	0.17	0.57	1.22	1.96
Unemployed – Women				
Cluster 1	−0.09	−1.00	−1.30	−2.38
Cluster 2	−1.23	−0.71	0.74	−1.19
Cluster 3	1.57	1.64	−1.56	1.65
Cluster 4	0.87	1.38	2.16	4.41
Employed – Men				
Cluster 1	−0.54	0.08	−0.77	−1.24
Cluster 2	−0.75	0.08	0.45	−0.22
Cluster 3	1.00	0.08	−0.74	0.34
Cluster 4	1.25	−0.39	1.51	2.37
Employed – Women				
Cluster 1	−0.07	−10.88	−0.32	−11.27
Cluster 2	−0.80	0.15	−0.50	−1.15
Cluster 3	−0.50	0.16	1.76	1.42
Cluster 4	1.80	0.21	0.34	2.35
Labor market group	Preferences	Intensity	Barriers	RELI

Source: Authors' elaboration.

interventions focusing on increasing the level of engagement in all dimensions. This implies interventions that would increase their level of education or provide them with job-specific skills, but also interventions that would change their attitudes toward work and help them with job searches. This profile is quite likely the hardest to activate. Paradoxically, unemployed women in cluster 1 have high reservation wages. Unemployed men in cluster 2 would benefit most from interventions that would increase their level of education or provide them with job-specific skills. On the other hand, unemployed women in cluster 2 would need behavioral interventions to change their mindsets about work. Cluster 3 would primarily require intermediation services, such as information on available job opportunities, job-search assistance, counselling, and support on how to prepare a resume or for an interview. Finally, those in cluster 4 are the easiest to activate.

Table 3 Clusters of unemployed men and women: profiles and interventions

	Profiles by engagement dimension				Intervention focus by engagement dimension			
	Preferences	**Intensity**	**Barriers**	**RELI**	**Preferences**	**Intensity**	**Barriers**	**Comments**
Unemployed Men								
Cluster 1	Well below	Below	Average	Well below	Attitude change	Job search motivation	Education and skills	Hardest to place; starting with regional focus is suggested
Cluster 2	Average	Above	Well below	Well below	Correcting expectations		Education, skills, and English	Young group; 90% are single
Cluster 3	Well above	Well below	Above	Average		Job search skills, counseling, etc.		Job intermediation and motivation
Cluster 4	Above	Well above	Above	Well above	Reservation wage and job attitude			Ready for the labor market but perhaps in different sectors
Unemployed Women								
Cluster 1	Average	Below	Well below	Well below	Attitude change	Job search motivation and skills	Education, skills, and gender barriers	Hardest to place as interventions required in all engagement dimensions
Cluster 2	Below	Above	Well below	Below		Intermediation services with focus on gender-adequate jobs	Interventions toward influencers	
Cluster 3	Well above	Well below	Well above	Above		Job search skills, counseling, placement assistance, etc.		Regional concentration
Cluster 4	Above	Well above	Well above	Well above				Ready for the labor market but demand may be missing; focus sector to be explored

Source: Authors' elaboration.

Table 3 raises three main observations: (i) measurement of engagement level by three independent dimensions allows developing interventions for each dimension separately; (ii) the level of the engagement dimension offers first indications on how much intervention is needed; and (iii) determination of specific interventions that are both needed and the most promising requires a deeper analysis of the survey results. Table 3 also suggests that not all engagement dimensions in all clusters require an individualized intervention. The lower the overall engagement index/cluster number, the more interventions are seemingly needed. This is the simple result that a lower-rated cluster signals deficiency in more than one or even all three dimensions. Higher-rated clusters require few or even no interventions.

4.2 Signaling Policy effectiveness and progress in engagement

The index may be used to signal progress in engagement and the effectiveness of interventions between two periods of time if the survey or the index-relevant subset of questions is repeated. For example, consider an intervention for unemployed women in cluster 1 to increase the intensity of job search. If the intensity of individuals is measured through the appropriate questions before and after the treatment, a measure of progress in the intensity dimension can be constructed. To this end, the weights of the pretreatment intensity measurement need to be fixed and applied to the posttreatment intensity measurement (as an out-of-sample observation). This is similar to a Laspeyres price index where the consumed quantities are kept constant to measure the price level change between a base period and the current period.

A hypothetical example is presented to describe the methodology. Consider the evaluation of a government intervention that aims to encourage women to update their CV more frequently. The methodology would be to randomly select two representative groups of women: a treatment group and a control group. The program is only implemented in the first group, but after a reasonable time, both groups have to answer the same questionnaire. In this case, the relevant questions are those used for the intensity dimension, defined as follows:

1. Actual applications: 1 if the individual has applied to a job, 0 otherwise.
2. CV updates: 1 if the CV has not been updated in a year, 2 if the CV has not been updated in a semester, 3 if the CV has not been updated in a month, 4 if the CV was updated last month.
3. Job search actions: Number of actions, from a list of nine that the individual has done frequently or very frequently.
4. Last application: 1 if there were no applications last year, 2 if there were no applications last semester, 3 if there were no applications last month, 4 if there was an application last month.
5. Number of applications: Number of applications made by the individual.
6. Recent search actions: Number of actions listed in question 3 done last month.
7. Job Seriousness: 1 if the job search is not very serious, 2 if it is somewhat serious, 3 if it is very serious.
8. Search Time: Number of hours per week dedicated to the job search.

Table 4 Baseline and assumptions on control and treatment outcomes

	Baseline (B)		Control (C)	Treatment (T)
Question	**Mean**	**SD**	**Mean**	**Mean**
Actual application	0.49	0.50	0.49	0.49
CV updates	1.68	1.59	1.68	3.00
Job search actions	0.76	1.31	1.20	1.60
Last application	1.44	1.63	1.44	1.44
Number of applications	1.32	2.48	1.32	1.32
Recent search actions	1.61	1.73	1.70	2.10
Job seriousness	2.61	0.49	2.61	2.90
Search time	3.97	5.39	3.97	5.00

Source: Authors' elaboration.

Table 4 shows the current baseline values of these questions as well as a hypothetical situation after an intervention takes place.

This example highlights two possibilities that can arise during the execution of the program. First, since people are encouraged to update their CV more often, they also end up increasing their search actions. Moreover, they invest more time in their job search and thus take it more seriously. For this reason, the means of five categories increase. Second, other events might take place outside the program. For example, Internet diffusion helps people to look for online jobs easily. Given that an Internet search is a type of search action, individuals can increase their search actions independent of their participation in the program if their access to the Internet improves. Hence, the treatment group can increase its search actions. Without having a control group, it would be very difficult to separate the program effect from other events happening in society.

Following the methodology presented in Section 2, the intensity dimension for both groups is calculated using the baseline, as depicted in Table 5:

Table 5 Intensity index calculator

	PCA score (W)	Standardized value control (SC)	Standardized value treatment (ST)	Weighted value control	Weighted value treatment
Formula		$\frac{\overline{x_C} - \overline{x_B}}{s_B}$	$\frac{\overline{x_T} - \overline{x_B}}{s_B}$	$\frac{W}{\sqrt{L}}SC$	$\frac{W}{\sqrt{L}}ST$
Actual application	0.49	0.00	0.00	0.00	0.00
CV updates	0.38	0.00	0.83	0.00	0.65
Job search actions	0.22	0.33	0.64	0.15	0.29
Last application	0.51	0.00	0.00	0.00	0.00
Number of applications	0.44	0.00	0.00	0.00	0.00
Resent search actions	0.24	0.05	0.28	0.03	0.14
Job seriousness	0.23	0.00	0.59	0.00	0.28
Search time	0.03	0.00	0.19	0.00	0.01
PCA variance (L)	0.24		**Intensity**	0.18	1.36

Source: Authors' elaboration.

1. The variable values are standardized using the mean and standard deviation of the baseline.
2. These values are multiplied by the PCA scores of the baseline and divided by the standard deviation of the PCA component.
3. These values are added together to calculate the new intensity value of each group.

The results from the hypothetical example show that:

- Overall, the intensity of the treatment group is now 1.36 standard deviations above the average of the baseline group.
- Of that, 0.18 standard deviations correspond to events that occurred out of the program. Hence, the program effect is the remaining 1.18 standard deviations.
- Whereas the program originally targeted CV updates, it has a positive spillover effect to other components of the dimension. Indeed, CV updates explain an increase of 0.65 standard deviations. The remaining 0.53 standard deviations are explained by the program's externalities.

5 Conclusions

This paper proposes an index to measure engagement on the labor market, an issue of critical importance to labor market outcomes and policies intended to improve them. The lower the level of labor market engagement and the higher the heterogeneity of the engagement among labor market groups are, the worse the labor market outcomes are likely to be. The proposed engagement index, RELI, enriches traditional measures of labor market outcomes in that it accounts for the heterogeneity of individuals' engagement levels within the employed, unemployed, and OLF categories based on three dimensions – preferences, intensity, and barriers. RELI is exemplified using data from a 2015/2016 labor market survey of nationals in the KSA, a country with a highly segmented and distorted labor market. Findings offer very useful insights about the engagement differences by age cohort and education level. For example, on average, younger people are more engaged in all dimensions than older people. For women, having a vocational degree rather than a bachelor's degree reduces barriers to labor market engagement.

The paper also presents a way in which the framework can be used to evaluate labor market policies and to target interventions. A clustering technique along the index dimensions is used to group individuals with similar levels of engagement. Applying it to the KSA data results in four clusters that call for differentiated interventions. For example, some clusters of the unemployed necessitate search assistance while others require upskilling. The index is thus a very useful instrument to: profile the employed, unemployed, and out-of-labor force and select interventions accordingly; design cluster-specific interventions; and measure engagement levels before and after interventions as a quick-and-dirty evaluation of their effectiveness.

The paper's main contribution is its capacity to create a multidimensional metric of engagement levels across labor market categories that integrate different engagement principles considered by the literature. To the best of the authors' knowledge, the multivariate statistical techniques applied in this research have not been used in labor market analyses so far. Traditional labor economic models assume that all individuals are willing to work if the

wage compensates at least the opportunity cost. By observing that the individuals' motivation depends on multiple dimensions, the paper constructs a conceptually grounded index that measures the individuals' engagement. Using this index, the paper demonstrates that the Saudi adult population is highly heterogeneous in its engagement level, such that different policies are required for each of the clustered profiles. An extension of the paper would be to apply the index to foreign labor in the KSA and other Gulf Cooperation Council (GCC) countries. The latter countries would be natural candidates to measure the level and differences of engagement among their national populations.

Declarations

Availability of data and material

Restrictions apply to the availability of the data used under license from the Saudi Ministry of Labor and Social Development for this study. Data are available from the authors upon reasonable request and with permission of the Saudi Ministry of Labor and Social Development only.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

All authors of this paper contributed equally. For writing purposes, Prof. Holzmann focused on the policy analysis and applicability of the current tool in labor market studies, Dr. Chartouni focused on the interpretation of the results for the Saudi context, and Dr. Paez focused on the multivariate analysis and the consistency between the statistical techniques and the conceptual framework. Besides the writing differentiation, all authors participated actively in each of the relevant discussions of the paper and approved the final manuscript.

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Annex

Mapped variables from the data by dimension and population group

Barriers

Identifier	Explanation	OLF	Unemployed	Employed	Men	Women
barriers_not_work	Self-identified reasons why the individual has no job	Yes	Yes	No	Yes	Yes
family_influence	Other members of the family have suggested the individual not to work	Yes	No	No	Yes	Yes
particular_barriers	Particular barriers that individuals face (looking for/during their) jobs	Yes	Yes	Yes	Yes	Yes
women_guardian_hours	Amount of hours that a guardian allows a woman to work	Yes	Yes	Yes	No	Yes
women_guardian_mixing	If the guardian allows mixing working environments	Yes	Yes	Yes	No	Yes
women_guardian_transport	Types of transport allowed by the guardian	Yes	Yes	Yes	No	Yes
women_guardian_work	If the guardian allows women to work	Yes	Yes	No	No	Yes
women_hours_housecare	Hours dedicated to household chores	Yes	Yes	Yes	No	Yes
women_housecare	Availability of a domestic worker	Yes	Yes	Yes	No	Yes
women_own_transport	Types of transport acceptable for women	Yes	Yes	Yes	No	Yes

Source: Authors' elaboration.

Preferences

Identifier	Explanation	OLF	Unemployed	Employed	Men	Women
attitude_requirements	Type of jobs that are considered acceptable	No	Yes	Yes	Yes	Yes
job_flexibility	Constraints on the jobs that the person is willing to accept	No	Yes	No	Yes	Yes
min_work_hours	Minimum hours that the person is willing to work	No	Yes	No	Yes	Yes
mixed_gender_environments	Does the working space have gender-mixing environments	No	No	Yes	Yes	Yes
reasons_not_working	Reasons why the individual is not working	Yes	Yes	No	Yes	Yes
relocate_willingess	Willingness to reallocate to find a job	No	Yes	No	Yes	Yes
women_mixing_thoughts	Attitude toward gender-mixing environments	Yes	Yes	Yes	No	Yes
women_work_attitude	Attitude toward women working	Yes	Yes	Yes	No	Yes
work_attitude	Attitude toward work	Yes	Yes	Yes	Yes	Yes
work_flex	Flexible working conditions	No	Yes	No	Yes	Yes
work_hours	Amount of working (or willing to work) hours	No	Yes	Yes	Yes	Yes
work_shifts	Willingness to do work shifts	No	Yes	No	Yes	Yes

Source: Authors' elaboration.

Intensity

Identifier	Explanation	OLF	Unemployed	Employed	Men	Women
actual_application	People that applied for jobs	No	Yes	No	Yes	Yes
cv_update	People that updated their CVs	No	Yes	No	Yes	Yes
do_shifts	People willing to do working shifts	No	No	Yes	Yes	Yes
extra_hours	Number of extra hours that people are willing to do	No	No	Yes	Yes	Yes
future_job_search	People willing to look for a job in the future	Yes	No	No	Yes	Yes
job_search_actions	Number of job search actions	No	Yes	No	Yes	Yes
last_applications	Time when the last application was done	No	Yes	No	Yes	Yes
last_search	Time when the last research was done	Yes	No	No	Yes	Yes
multiple_job	Identify people with multiple jobs	No	No	Yes	Yes	Yes
num_applications	Number of applications done by the individual	No	Yes	No	Yes	Yes
recent_search_actions	Number of recent search actions done	No	Yes	No	No	No
search_time	Hours dedicated to job search	No	Yes	No	Yes	Yes
serious_job_search	How serious is the job search	No	Yes	No	Yes	Yes

Source: Authors' elaboration.

Dimension indices

Weights of each of the PCAs performed for the three dimensions and the overall index.

				Pearson		Spearman	
Work status	**Gender**	**Dimension**	**Variables**	**PC1**	**PC2**	**PC1**	**PC2**
OLF	**Men**	**Barriers**	Component Variance	0.28	0.48	0.28	0.48
		1	barriers_not_work_10	0.43	0.01	0.43	0.01
		2	particular_barriers_2	0.53	0.03	0.53	0.03
		3	particular_barriers_3	0.45	0.05	0.45	0.05
		4	particular_barriers_4	0.57	0.03	0.57	0.03
		5	family_influences	−0.06	1	−0.06	1
		Intensity	Component Variance	0.54	1	0.54	1
		1	last_search	0.71	0.71	0.71	0.71
		2	future_job_search	0.71	−0.71	0.71	−0.71
		Preferences	Component Variance	0.65	1	0.65	1
		1	reasons_not_working	0.71	0.71	0.71	0.71
		2	work_attitude	0.71	−0.71	0.71	−0.71

(*continued*)

				Pearson		Spearman	
Work status	**Gender**	**Dimension**	**Variables**	**PC1**	**PC2**	**PC1**	**PC2**
	Women	**Barriers**	Component Variance	0.12	0.23	0.12	0.23
		1	barriers_not_work_6	0.26	0.04	0.24	0.02
		2	barriers_not_work_10	0.23	−0.37	0.22	−0.41
		3	particular_barriers_2	0.33	−0.33	0.31	−0.36
		4	particular_barriers_3	0.23	−0.33	0.22	−0.37
		5	particular_barriers_4	0.42	−0.23	0.38	−0.26
		6	particular_barriers_9	0.06	−0.02	0.04	−0.01
		7	women_guardian_mixing	0.26	0.01	0.25	0.04
		8	women_guardian_transport	0.4	0.25	0.43	0.24
		9	women_own_transport	0.35	0.28	0.39	0.27
		10	women_guardian_work	0.15	0.43	0.15	0.37
		11	women_housecare	0.2	0.04	0.26	0.07
		12	women_hours_housecare	0.21	−0.04	0.24	−0.01
		13	family_influences	0.29	0.36	0.27	0.31
		14	women_guardian_hours	−0.03	0.37	0	0.35
		Intensity	Component Variance	0.53	1	0.54	1
		1	future_job_search	0.71	0.71	0.71	0.71
		2	last_search	0.71	−0.71	0.71	−0.71
		Preferences	Component Variance	0.37	0.61	0.38	0.62
		1	reasons_not_working	0.58	0.34	0.59	0.25
		2	women_mixing_thoughts	0.4	−0.9	0.39	−0.85
		3	women_work_attitude	0.43	0.27	0.43	0.45
		4	work_attitude	0.56	0.08	0.56	−0.02
Unemployed	**Men**	**Barriers**	Component Variance	0.31	0.53	0.31	0.53
		1	barriers_not_work_10	0.36	0.57	0.36	0.57
		2	particular_barriers_2	0.51	0.38	0.51	0.38
		3	particular_barriers_3	0.5	−0.13	0.5	−0.13
		4	particular_barriers_4	0.51	−0.23	0.51	−0.23
		5	particular_barriers_8	0.32	−0.68	0.32	−0.68
		Intensity	Component Variance	0.23	0.4	0.23	0.4
		1	actual_applications	0.52	0.29	0.5	0.3
		2	cv_update	0.38	−0.19	0.37	−0.15
		3	job_search_actions	0.14	−0.51	0.2	−0.49
		4	last_applications	0.53	0.26	0.5	0.25
		5	num_applications	0.46	0.11	0.48	0.21
		6	recent_search_actions	0.24	−0.43	0.24	−0.43
		7	serious_job_search	0.09	−0.41	0.1	−0.46
		8	search_time	0.12	−0.44	0.17	−0.37
		Preferences	Component Variance	0.16	0.3	0.17	0.31
		1	job_flexibility	0.36	0.18	0.44	0.04
		2	min_work_hours	0.56	−0.27	0.53	−0.08
		3	reasons_not_working	0.02	0.59	−0.09	0.53
		4	work_flex	0.2	0.18	0.3	−0.05
		5	work_hours	0.56	−0.23	0.54	0
		6	work_shift	0.17	0.49	0.12	0.52
		7	relocate_willingess	0.12	−0.07	0.08	−0.16
		8	work_attitude	0.07	0.43	−0.1	0.57
		9	attitude_requirements	0.41	0.16	0.33	0.29

(*continued*)

				Pearson		Spearman	
Work status	**Gender**	**Dimension**	**Variables**	**PC1**	**PC2**	**PC1**	**PC2**
	Women	**Barriers**	Component Variance	0.1	0.2	0.11	0.2
		1	barriers_not_work_5	0.04	0.15	0.03	0.16
		2	barriers_not_work_6	0.26	0.19	0.21	0.26
		3	barriers_not_work_10	0.12	0.43	0.13	0.41
		4	particular_barriers_2	0.24	0.38	0.23	0.35
		5	particular_barriers_3	0.18	0.38	0.14	0.34
		6	particular_barriers_4	0.08	0.42	0.06	0.41
		7	particular_barriers_8	−0.04	0.17	−0.03	0.16
		8	particular_barriers_9	0.17	−0.23	0.14	−0.15
		9	women_guardian_hours	0.11	−0.17	0.24	−0.29
		10	women_guardian_mixing	0.38	0	0.42	0
		11	women_guardian_transport	0.53	−0.24	0.5	−0.26
		12	women_own_transport	0.55	−0.19	0.51	−0.21
		13	women_guardian_work	0.18	−0.17	0.14	−0.06
		14	women_housecare	0.06	0.21	0.06	0.19
		15	women_hours_housecare	0.13	0.1	0.26	0.25
		Intensity	Component Variance	0.24	0.39	0.25	0.41
		1	actual_applications	0.49	0.23	0.51	0.16
		2	cv_update	0.38	0.17	0.37	0.12
		3	job_search_actions	0.22	−0.52	0.14	−0.62
		4	last_applications	0.51	0.22	0.52	0.16
		5	num_applications	0.44	0.01	0.48	0.1
		6	recent_search_actions	0.24	−0.46	0.21	−0.56
		7	serious_job_search	0.23	−0.24	0.2	−0.11
		8	search_time	0.03	−0.57	0.06	−0.46
		Preferences	Component Variance	0.15	0.26	0.15	0.26
		1	job_flexibility	0.3	0.44	0.36	0.22
		2	min_work_hours	0.52	−0.24	0.5	−0.15
		3	reasons_not_working	0.05	0.14	0	0.04
		4	women_mixing_thoughts	0.36	0.11	0.39	−0.07
		5	women_work_attitude	0.09	0.42	0.07	0.45
		6	work_flex	0.21	0.59	0.2	0.52
		7	work_hours	0.49	−0.24	0.49	−0.05
		8	work_shift	0.29	−0.1	0.25	−0.32
		9	relocate_willingess	0.13	−0.16	0.2	−0.37
		10	work_attitude	0.33	−0.17	0.28	0.11
		11	attitude_requirements	−0.03	−0.28	−0.07	−0.44
Employed	**Men**	**Barriers**	Component Variance	0.52	0.84	0.52	0.84
		1	particular_barriers_2	0.41	0.91	0.41	0.91
		2	particular_barriers_3	0.65	−0.24	0.65	−0.24
		3	particular_barriers_4	0.64	−0.34	0.64	−0.34
		Intensity	Component Variance	0.36	0.69	0.38	0.71
		1	multiple_job	0.37	0.91	0.32	0.93
		2	extra_hours	0.68	−0.14	0.69	−0.1
		3	do_shifts	0.64	−0.38	0.65	−0.36

(*continued*)

				Pearson		Spearman	
Work status	**Gender**	**Dimension**	**Variables**	**PC1**	**PC2**	**PC1**	**PC2**
		Preferences	Component Variance	0.29	0.54	0.3	0.55
		1	work_hours	0.35	0.73	0.45	0.6
		2	mixed_gender_environment	0.58	−0.3	0.53	−0.41
		3	work_attitude	−0.51	0.51	−0.49	0.55
		4	attitude_requirements	0.54	0.34	0.52	0.41
	Women	**Barriers**	Component Variance	0.16	0.31	0.16	0.32
		1	particular_barriers_2	0.6	0.06	0.59	0.1
		2	particular_barriers_3	0.56	0.06	0.55	0.1
		3	particular_barriers_4	0.44	0.06	0.44	0.08
		4	particular_barriers_8	0.36	0.01	0.35	0.04
		5	women_guardian_hours	0	−0.37	0.01	−0.4
		6	women_guardian_mixing	0.01	−0.38	0.02	−0.37
		7	women_guardian_transport	0.07	−0.58	0.12	−0.56
		8	women_own_transport	0.09	−0.6	0.14	−0.57
		9	women_housecare	0.01	−0.12	0.01	−0.12
		10	women_hours_housecare	−0.02	0.01	0	−0.15
		Intensity	Component Variance	0.34	0.68	0.35	0.68
		1	multiple_job	0.55	0.62	0.54	0.68
		2	extra_hours	0.4	−0.79	0.52	−0.73
		3	do_shifts	0.73	−0.04	0.66	0.02
		Preferences	Component Variance	0.23	0.41	0.24	0.42
		1	women_mixing_thoughts	0.55	0.08	0.53	0.01
		2	women_work_attitude	0.53	0.2	0.51	0.3
		3	work_hours	0.28	−0.54	0.37	−0.44
		4	mixed_gender_environment	0.56	0.01	0.53	−0.04
		5	work_attitude	−0.15	0.26	−0.2	0.03
		6	attitude_requirements	−0.04	−0.77	−0.04	−0.85

Source: Authors' elaboration.

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