Social Capital and Workers' Job Prospects in the MENA Region*

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Abstract: Social networks and collective trust have been studied in relation to civil uprisings such as the Arab Spring events of 2011. Social capital is also an important factor in the Middle East and North African (MENA) labour markets, where 'wasta' family connections are said to affect workers' opportunities. Little is known, however, about MENA citizens' social capital and its composition and distribution across socio-economic groups. As an advanced foundation on which to build future analyses, we propose a stochastic approach for measuring people's social capital using Bayesian clustering, based on three dimensions: level of social activity, quality of social networks, and trust. Applying the method to the 2000–2014 World Values Surveys for 16 MENA countries, we describe the composition and distribution of workers' social capital within and between countries, and estimate ordered-probability regressions of workers' employment outcomes as a function of the dimensions of social capital, workers' demographics, and subjective health assessment. We find that, among the three dimensions of social capital, social trust is most clearly conducive to the employment and full-time status of both genders. The level of social activity is associated with more autonomous, intellectual and creative occupations among men, but only with more creative occupations among women. Higher-quality social networks are associated with more autonomous jobs, but also less creative ones. Interestingly, trust is associated with non-autonomous, manual, and routine jobs. In creative jobs favoured by the Fourth Industrial Revolution, workers are selected from those with higher socializing levels but inhibited networks and trust.

Keywords: employment vulnerability, Middle East and North Africa, social capital, World Values Surveys

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Motivation

Much has been written about the precariousness of employment conditions in the Middle East and North African (MENA) region, particularly among marginally attached groups, including fresh graduates and women [e.g. Ozturkler 2014; Fehling et al. 2016; Chen and Harvey 2017]. Numerous empirical studies have assessed the sources of the inequitable and unbalanced state of the labour markets [e.g. Assaad 2014; Krafft and Assaad 2016], highlighting the role of market barriers and unfair competition between formal and informal establishments, low labour productivity, ineffective skill acquisition, and false expectations of labour market prospects [Assaad et al. 2018]. These studies have largely overlooked the role of social capital beyond mentioning the benefits of political connections among firms allied with the ruling regimes [Diwan et al. 2016, 2019; Aly and Abdel-Latif 2018; Francis et al. 2018; Kubinec 2018], the role of workers' *wasta* in organisations' recruiting [Marktanner and Wilson 2016; Ta'Amnha et al. 2016; Alsarhan and Valax 2021; Alsarhan et al. 2021], or the influence of parental attributes, resources, and connections on workers' prospects [AlAzzawi and Hlasny 2019, 2022a,b].

The concept of social capital has itself remained out of the domain of economics until recently. Its relevance to individuals' and communities' wellbeing has traditionally been investigated in sociology [Coleman 1994; Portes 1998; Putnam 2000; Siisiäinen 2003; Antoci et al. 2007; Fukuyama 2001; Helliwell et al. 2017a]. Bourdieu [1986: 248–249] defined it as 'the aggregate of the actual or potential resources which are linked to [...] membership in a group – which provides each of its members with the backing of the collectivity-owned capital'. Social capital is a multidimensional attribute of individuals and their community that interacts with individuals' human and physical capital to produce various real lifetime outcomes. Social capital includes individuals' soft skills, such as trust in public and market institutions, sociability in particular social contexts, and size and quality of individuals' social networks. Different individuals accumulate different amounts and forms of social capital and collect different economic and non-economic benefits from their investments [Knack and Keefer 1997; Astone et al. 1999].

Only in the past two decades, economists have gradually embraced social capital upon recognising that factors besides the accumulation of hard skills and physical capital affect individuals' economic performance and life satisfaction [Helliwell et al. 2017b]. Even at the societal level, social capital has been found to correlate with economic development [Fukuyama 2001; Pérez García et al. 2008]. Individuals' sociability and social networking affect their labour-market, financial, and other lifetime outcomes, their welfare, as well as the outcomes of their offspring [Hofferth et al. 1998] and societal outcomes [DiPasquale and Glaeser 1999]. Individuals' norms and the values they attribute to their possessions and outcomes affect their incentives to invest, as well as their life satisfaction. Hence, social capital has multiple roles in individuals' pursuit of their career and lifetime goals, and in the functioning of communities and societies.

In MENA countries, ethnic and cultural homogeneity facilitate the formation of social capital and markets' reliance on it for conducting transactions, such as matching workers with employers [Alesina and LaFerrara 2000]. The role of people's social networks and social media's mobilisation of them has been highlighted in relation to the dynamics of the Arab Spring events of 2011 and their suppression in the following years. To this day, the use of social media is curtailed by the authorities in much of the region. Even before the Arab Spring, the 'Arab inequality puzzle' attracted worldwide interest for the apparent incongruity between the growing social discontent and the evidence of rather equitable distributions of surveyed economic outcomes. Academic attention shifted to niche facets of socio-economic inequality such as subjective perceptions of inequality, performance of reference groups such as top earners, and the distribution of physical capital [Hlasny and AlAzzawi 2019; Hlasny 2020; ESCWA 2020, 2022]. Social capital is also an important factor in labour and procurement markets, particularly in the informal MENA economies where family resources and connections (*wasta*) have been found to affect young workers' employment prospects and to give rise to significant inequality of opportunities [AlAzzawi and Hlasny 2022a,b]. Given the latent nature and multidimensionality of social capital, the following elusive questions endure: What is social capital composed of, and how is it distributed across MENA countries' populations? What determines the regional levels and between-group gaps in social capital? And how do they interact with workers' economic prospects and outcomes?

Social capital is unobservable and must be estimated indirectly. Yet, existing economic literature provides limited guidance on how to incorporate social capital in economic analyses, particularly in the world's understudied regions. Social capital is still largely treated as a sociological construct, and few studies link social capital acquisition to individuals' economic decisions and outcomes. Investigative methods for the estimation of social capital are lacking, particularly compared to the strides recently made in measuring individuals' human capital, wealth, or even happiness. Moreover, the vast bulk of literature assumes individuals' social capital to be exogenously given, and few existing works consider its endogeneity and the mechanisms of its formation. Our study contributes on this front.

In the MENA region, the distribution of social capital and its implications for the economic and political status quo have received surprisingly little attention. The nature of MENA citizens' social engagement, the distribution of social-capital dimensions across various socio-economic groups and countries, and the evolution of the distribution over time are all unclear. Some MENA countries have been chronically understudied even in relation to their basic labour market functioning and workers' fates, such as Iran (a notable exception is Egel and Salehi-Isfahani [2010]).

This paper aims to contribute to filling these multiple gaps. We propose an advanced Bayesian approach for clustering indicators of three dimensions of social capital – level of social activity, social networks, and trust – to estimate three unidimensional indices of each dimension of social capital, as an alternative to the more commonly applied weighted-sum, average, principal component, finite-mixture imputations, or deterministic clustering [Hlasny and Lee 2020]. We describe the composition of social capital by its dimensions, and their distribution within and across 16 MENA countries over the span of the years 2000–2014. We then investigate how the dimensions of social capital affect workers' employment outcomes.

The rest of the study is organised as follows. The next section introduces the proposed methodology and data used. The section following that presents the key results, and the last section concludes with suggestions for public policy and for future investigations.

Methods and data

This study applies the lessons from the literatures on social-capital modelling and on the MENA-region labour markets to investigate the effect of workers' social capital on their labour market outcomes. We contribute by explicitly accounting for three dimensions of workers' social capital in the regressions of workers' employment status. The key hypothesis evaluated in this study is that, across MENA labour markets, workers' multiple facets of social capital all exert positive effects on workers' employment outcomes, even after controlling for workers' other characteristics and backgrounds. Due to the latent nature of social capital and the categorical nature of employment outcomes, this exercise requires advanced treatment, which is described below.

Imputing social capital by non-hierarchical Bayesian clustering

Social capital is unobservable, and its empirical measurement depends on how we define it conceptually. In this paper, we classify social capital by its three distinct dimensions as recognised in the literature [see the references in Hlasny and Lee 2020]: level of social activity, perceived quality of one's social network, and the degree of trust in social institutions. These three dimensions of social capital must be imputed and used in regressions in tandem.

The level of social activity covers a person's active engagement with political parties and environmental, professional, humanitarian, or other social organisations. Also, it encompasses the frequency of one's meetings with friends, parents, or relatives, active or passive participation in sports, culture, and community or religious organisations, and attendance at religious services.

The quality of one's social network covers how often one receives information from friends or colleagues, to what extent one regards oneself as a member of a local community or a citizen of one's country, and one's membership in professional associations. Finally, trust in social institutions gauges an individual's view on whether most people can be trusted, and how much one trusts one's family, neighbours, long-time contacts, first-time acquaintances, or people of another religion. It also encompasses how much one trusts the media, government, political parties, and major companies, and how confident one is in the justice system/courts, charitable/humanitarian organisations, banks, and universities. Table 1 lists the variables for the respective dimensions of social capital used in our clustering exercise. Their detailed definitions are documented by Inglehart et al. [2014].

To define the (dis)similarities in individuals' profiles of social activity (social network or trust, respectively) and identify patterns in data, we constructed a weighted index of the latent value of this variable for individuals using the Gaussian mixture model by means of Bayesian clustering as proposed by Franzen [2006].[1]

Bayesian clustering takes a stochastic view of the determination of workers' socialising, social networks, and trust, respectively, and allows us to make probability-weighted predictions of individuals' true values. To this end, we group the values of the various social-capital indicators into distinct clusters, using their observed joint distribution. In all the clusters we identify the representative datapoints or centroids. We then use the Bayesian approach to estimate the probabilities of individuals' belonging to each cluster and predict the weighted index of the dimension of social capital by multiplying the estimated probabilities by the mean value for each cluster (centroid).

The strength of Bayesian clustering relative to conventional deterministic imputation (including parametric finite mixture models, and principal component analysis) is that it allows for uncertainty about how to classify and treat each individual, meaning that the individual may have come from any cluster only subject to different probabilities. Bayesian clustering does not pinpoint de-

[1] This is a model-based non-hierarchical clustering technique based on a Markov Chain Monte Carlo (MCMC) method. This technique is more advantageous than the usual model-based clustering using Expectation Maximisation (EM) algorithms, since MCMC is known to be empirically 'preferable over EM algorithm in recovering the parameters of mixture models, in particular if the shape of the likelihood surface is problematic, exhibiting ridges, flat regions and/or saddle points' [Dias and Wedel 2004]. Although the data are of a categorical scale, we consider using scores for the ordinal predictors following prior literature [Labovitz 1970, 1971; Mayer 1971; O'Brien 1979; Brockett 1981; Golden and Brockett 1987; Agresti 2002; Chen and Wang 2014]. That is, we transform the ordinal data into an interval scale by assigning scores so that more general statistical approaches can be used. Moreover, we interpret the predictors' scale as continuous and impute missing values in the dimensions of social capital by the average of individuals with similar socioeconomic characteristics: workers with the same survey year, age, sex and education. This way we can expand the data spectrum to be continuous, and we can apply the Gaussian mixture model by Bayesian clustering.

Table 1. Summary statistics of social capital indicators by country group & gender – first part

	Gulf Cooperation Council (GCC)		Middle income		Low income	
	Men	Women	Men	Women	Men	Women
Number of observations	1915	1593	12 192	13 668	667	685
Social capital dimension 1: Level of social activity						
Active level in religion	0.271	0.216	0.086	0.069	0.192	0.165
	(0.616)	(0.566)	(0.365)	(0.330)	(0.504)	(0.472)
Active level in sports or recreation	0.287	0.176	0.105	0.060	0.202	0.080
	(0.626)	(0.508)	(0.408)	(0.305)	(0.536)	(0.302)
Active level in art, music, and education	0.183	0.218	0.051	0.052	0.097	0.080
	(0.519)	(0.575)	(0.284)	(0.287)	(0.361)	(0.321)
Active level in a political party	0.000	0.000	0.054	0.028	0.445	0.175
	(0.000)	(0.000)	(0.284)	(0.199)	(0.728)	(0.460)
Active level in an environmental organisation	0.167	0.129	0.035	0.026	0.069	0.067
	(0.501)	(0.436)	(0.224)	(0.196)	(0.297)	(0.283)
Active level in a professional organisation	0.253	0.194	0.069	0.040	0.190	0.092
	(0.592)	(0.541)	(0.321)	(0.244)	(0.512)	(0.340)
Active level in a humanitarian organisation	0.263	0.233	0.079	0.064	0.177	0.140
	(0.619)	(0.585)	(0.357)	(0.321)	(0.501)	(0.434)
Active level in any other organisation	0.040	0.042	0.014	0.015	0.033	0.019
	(0.253)	(0.253)	(0.152)	(0.155)	(0.202)	(0.157)
How often a respondent discusses political matters with friends	0.264	0.293	0.318	0.210	0.000	0.000
	(0.548)	(0.603)	(0.588)	(0.478)	(0.000)	(0.000)

Table 1. Summary statistics of social capital indicators by country group & gender – second part

	Gulf Cooperation Council (GCC)		Middle income		Low income	
	Men	Women	Men	Women	Men	Women
Number of observations	1915	1593	12 192	13 668	667	685
How often respondent attends religious services	0.835	0.623	1.302	0.799	1.856	0.572
	(0.944)	(0.860)	(0.871)	(0.850)	(0.469)	(0.825)
How often respondent spends time with friends	0.543	0.582	0.58	0.482	0.000	0.000
	(0.882)	(0.898)	(0.895)	(0.837)	(0.000)	(0.000)
Frequency spending time with parents or other relatives	0.527	0.575	0.595	0.541	0.000	0.000
	(0.867)	(0.891)	(0.897)	(0.873)	(0.000)	(0.000)
Frequency spending time with people at a sports, cultural, or communal organisation	0.351	0.225	0.107	0.045	0.000	0.000
	(0.715)	(0.578)	(0.425)	(0.281)	(0.000)	(0.000)
Frequency spending time with people at your church, mosque, or synagogue	0.478	0.288	0.314	0.134	0.000	0.000
	(0.829)	(0.657)	(0.711)	(0.480)	(0.000)	(0.000)
Social capital dimension 2: Network						
Information source: talk with friends or colleagues	1.271	1.190	0.463	0.435	1.702	1.463
	(0.885)	(0.911)	(0.830)	(0.806)	(0.646)	(0.807)
I see myself as a citizen of the country	1.055	1.068	0.748	0.904	1.520	1.364
	(0.896)	(0.904)	(0.855)	(0.895)	(0.607)	(0.610)
I see myself as a member of my local community	0.989	1.009	0.852	0.796	1.398	1.208
	(0.894)	(0.885)	(0.904)	(0.853)	(0.604)	(0.609)
I see myself as someone who is outgoing, sociable	0.753	0.527	0.351	0.356	1.811	1.364
	(0.926)	(0.835)	(0.729)	(0.727)	(0.511)	(0.610)

Table 1. Summary statistics of social capital indicators by country group & gender – third part

	Gulf Cooperation Council (GCC)		Middle income		Low income	
	Men	Women	Men	Women	Men	Women
Number of observations	1915	1593	12 192	13 668	667	685
Social capital dimension 3: Trust						
How much do you trust your family?	1.235	1.170	0.906	0.982	1.905	1.746
	(0.903)	(0.902)	(0.983)	(0.984)	(0.349)	(0.590)
How much do you trust television?	0.856	0.932	0.578	0.707	0.363	1.874
	(0.783)	(0.796)	(0.718)	(0.747)	(0.570)	(0.396)
How much do you trust the government?	0.756	0.755	0.613	0.652	0.374	0.394
	(0.816)	(0.842)	(0.771)	(0.776)	(0.633)	(0.583)
How much do you trust political parties?	0.000	0.000	0.237	0.229	0.162	0.431
	(0.000)	(0.000)	(0.529)	(0.518)	(0.417)	(0.634)
How much do you trust major companies?	0.810	0.884	0.414	0.420	0.272	0.190
	(0.771)	(0.777)	(0.649)	(0.645)	(0.515)	(0.450)
How much do you trust your neighbourhood?	0.791	0.660	0.576	0.611	1.165	0.242
	(0.794)	(0.739)	(0.779)	(0.779)	(0.684)	(0.496)
How much do you trust people you know personally?	0.814	0.806	0.550	0.594	1.022	0.941
	(0.801)	(0.805)	(0.766)	(0.774)	(0.679)	(0.698)
How much do you trust people you meet for the first time?	0.347	0.307	0.117	0.121	0.198	0.200
	(0.576)	(0.554)	(0.357)	(0.359)	(0.424)	(0.438)
How much do you trust people of another religion?	0.390	0.359	0.170	0.162	0.180	0.118
	(0.593)	(0.571)	(0.424)	(0.411)	(0.428)	(0.339)

Table 1. Summary statistics of social capital indicators by country group & gender – fourth part

	Gulf Cooperation Council (GCC)		Middle income		Low income	
	Men	Women	Men	Women	Men	Women
Number of observations	1915	1593	12 192	13 668	667	685
Confidence level in justice system/courts	0.896	0.861	0.389	0.404	0.369	0.434
	(0.863)	(0.869)	(0.693)	(0.701)	(0.608)	(0.628)
Confidence level in charitable or humanitarian organisations	0.763	0.716	0.429	0.489	0.495	0.535
	(0.804)	(0.803)	(0.701)	(0.736)	(0.643)	(0.671)
Confidence level in banks	0.624	0.642	0.205	0.199	0.334	0.363
	(0.774)	(0.783)	(0.525)	(0.510)	(0.580)	(0.625)
Confidence level in universities	0.707	0.720	0.225	0.229	0.584	0.602
	(0.794)	(0.813)	(0.542)	(0.547)	(0.643)	(0.682)

Notes: Authors' analysis based on the World Values Survey, waves 4–6.

terministically a specific cluster that a given individual must be coming from, and it produces more robust predictions accompanied by the estimates of the associated uncertainty [Franzen 2006; Muller et al. 2009].

The stochastic technique allows us to arrive at more generalised predictions of social engagement for any individual or any profile of behaviour, and even allows us to identify probabilistic outliers – something that deterministic imputation methods could not do in the absence of information on how to evaluate distances across distinct profiles of social capital. Moreover, compared to hierarchical clustering approaches, our non-hierarchical clustering adopts the information structure from the unstructured but *proper* prior distributions of the variables of interest, and is expected to be more efficient [Franzen 2006]. (The technical specification of the method is presented in the appendix.)

Setting the count of clusters

Our clustering approach proceeds from a pre-set number of clusters that appears consistent with the peaks and other features in our data. For each dimension of social capital, we compute a simple average of workers' values for all available indicators and plot a distribution across workers. (The total sum of values for all indicators is used as an alternative.) We observe that the level of social activity and the quality of social networks and trust exhibit a large number of distinct peaks across workers. We can interpret these initial counts as the maximum number of clusters for each dimension of social capital, since it would be unlikely to identify clusters beside those marked by the peaks in the raw data. However, these numbers may not represent the true distinct profiles of social engagement across individuals – in terms of their types and degrees – and may not be efficient for the performance of the structural model of employment effects. The reason is that the set of clusters may exhibit redundancy in terms of the composition of indicator values in each cluster. We thus rely on the Bayesian Information Criterion (BIC) to identify the most efficient clustering and the optimal number of clusters for each dimension of social capital. The BIC has several statistical strengths: it chooses the most parsimonious model because it imposes a penalty on complex models with many parameters [Bishop 2006] and in large datasets it selects the correct model with a probability of one [Hastie, Tibshirani and Friedman 2016].

Estimating employment effects

Using the imputed values of the three dimensions of social capital, we can estimate their effects on individuals' employment outcomes. Because of the categorical nature of the alternative employment outcomes and the ordinal relations between them, we applied ordered probabilistic regression models. Moreover, because individuals' social engagement may be endogenous to their labour market choices and attainments, we attempt to extract only the exogenous parts of the social-capital dimensions through an instrumental variable (IV) approach. Our structural regression model thus consists of two stages: in the first stage, we estimate linear IV regressions predicting the values of the three dimensions of social capital using exogenous factors. In the second stage, we estimate probabilistic (probit and ordered probit) regressions of the alternative employment outcomes on the instrumented values of social-capital dimensions.

For the dependent variable in our structural model, workers' employment outcomes come from an ordinal spectrum of categorical statuses, measured using several alternative indicators. As a benchmark, we use the binary indicators *employed vs non-employed*$_{\mathrm{it}}$ (model A), where the former group includes full-/part-time wage workers and the self-employed, while the latter includes the unemployed actively searching for employment and those out of the labour force (including housewives). Since in the MENA region the vast majority of adult men are employed, but at the same time many men and some women are underemployed, we next use a more regionally tailored dependent variable: *full-time wage vs part-time wage/self-employed*$_{\mathrm{it}}$ workers (model B). In both of these specifications, the latter status (i.e. non-employed, part-time/self-employed) is considered the baseline or natural outcome. This is because this kind of precarious status – less rewarding in terms of compensation and benefits and overall less desirable to most workers – is widespread among new labour market entrants [Hlasny and AlAzzawi 2022].

Digging deeper into the nature of people's work, we consider an ordered categorical indicator of how autonomous one's job is on an ordinal scale of 1–10 (model C: no independence 1 – complete independence 10), allowing for heterogeneous effects of the social capital dimensions across jobs with different degrees of autonomy. Similarly, we consider ordered categorical indicators for how intellectual (model D: mostly manual 1 – mostly intellectual 10) and creative (model E: mostly routine 1 – mostly not routine 10) workers' tasks are in their main jobs. Each of these three dependent variables is thus on a scale from 1 to 10, where 1 is the least preferred outcome and is the baseline in the ordered-probit regressions. Coefficients in the models can be interpreted as the increases in the workers' prospect of exiting precarious and dreary positions for steadier and more stimulating ones.

In the first stage, we run an ordinary least squares (OLS) regression for the following equation:

$$SC_{ij} = Z_i'\delta + X_{i1}'\gamma + v_i, \qquad j = 1, 2, 3;\ i = 1, 2, 3, \ldots, n.$$

In the second stage, we run a probit model for the binary dependent variable with the equation

$$Employment_{\mathrm{i}} = \widehat{SC_{\iota 1}}\beta_1 + \widehat{SC_{\iota 2}}\beta_2 + \widehat{SC_{\iota 3}}\beta_3 + X_{i1}'\alpha + u_i, \qquad i = 1, 2, 3, \ldots, n,$$

with the predicted probabilities

$$P(Employment_i = 1|\widehat{SC_{i1}}, \widehat{SC_{i2}}, \widehat{SC_{i3}}\ X_{2i}) = \Phi(\widehat{SC_{i1}}\beta_1 + \widehat{SC_{i2}}\beta_2 + \widehat{SC_{i3}}\beta_3 + X'_{2i}\alpha),$$

or we estimate an ordered probit model for the ordinal dependent variable with

$$\begin{aligned} P(Nature\ of\ Jobs_i = m|\widehat{SC_{i1}}, \widehat{SC_{i2}}, \widehat{SC_{i3}}\ X_{2i}) \\ = \Phi(\lambda_m - \widehat{SC_{i1}}\beta_1 - \widehat{SC_{i2}}\beta_2 - \widehat{SC_{i3}}\beta_3 - X'_{2i}\alpha) \\ - \Phi(\lambda_{m-1} - \widehat{SC_{i1}}\beta_1 - \widehat{SC_{i2}}\beta_2 - \widehat{SC_{i3}}\beta_3 - X'_{2i}\alpha). \qquad & i = 1, \dots, n; \\ & m = 1, \dots, 10. \end{aligned}$$

Here $SC_{ij}(j = 1, 2, 3)$ denotes the j^{th} dimension of social capital. One's level of *social activity* is the first type ($j = 1$); one's accumulated value or gain from forming a *network* is the second ($j = 2$); and one's *trust* in various types of institutions is the third ($j = 3$). Z_{ij} denotes instrumental variables for social capital and X_{i1} denotes the exogenous regressors used in instrumenting, while $\widehat{SC_{ij}}$ indicates the predicted values of the dimensions of social capital. The disturbance terms (u_i, v_i) are assumed to be bivariate normal as $N\left(\begin{pmatrix}0\\0\end{pmatrix}, \begin{pmatrix}\delta_u^2 & \delta_{uv}\\ \delta_{vu} & \delta_v^2\end{pmatrix}\right)$, where σ_{uv} may be nonzero.

In the first-stage linear regressions, X_{1i} includes the individual's education, subjective health status, age, age squared, town size (small ~2000–5000; intermediate 5000–20 000; medium 20 000–100 000; large 100 000+), country income level (Gulf Cooperation Council, middle-income country, or low-income country[2]), and a linear time trend. These factors are assumed to be exogenous in the first-stage model. This appears to be justified theoretically for most variables: Education up to the incomplete secondary level is exogenous by default, since it is prescribed by government policy. Health is also likely exogenous since it is influenced by workers' demographics (age, gender) and physical attributes.

[2] The most fundamental way to classify the economies and labour markets in the MENA region is according to the national level of economic development in terms of real purchasing-power-parity adjusted incomes. Incidentally, this approximately agrees with the traditional geographic grouping of MENA countries. The United Nations and the World Bank classify the Gulf Cooperation Council countries in the Arabian Peninsula as high income (here: Bahrain, Kuwait, Qatar, Saudi Arabia); the vast majority of the region across Maghreb and Mashreq subregions as middle-income countries (here Algeria, Egypt, Iraq, Jordan, Lebanon, Libya, Morocco, Tunisia, Iran, Turkey); and a handful of impoverished and conflict-affected countries mostly in East Africa as low-income countries (here Palestine, Yemen). These three country groups have differently organised labour markets, with different distributions of occupations and employment types, suggesting that workers' attributes including social capital may be associated differently with the levels on the job ladder.

In the second-stage probabilistic regressions, the main independent variables of interest are the three instrumented dimensions of social capital, and the set of controls (X_{2i}) includes the same variables as in the first stage, with several exceptions: education level is subdivided into more detailed levels, and one's marital status (married, divorced/separated, or single/never married) is added. The main impacts of interest are the marginal effects of the predicted dimensions of social capital, derived from their second-stage coefficients.

Acknowledging the notorious gender gaps in the regional labour markets, the models are estimated separately for each gender to avoid biases in the estimated effects, inefficiency due to heteroskedasticity, and other potential issues.

Data

The paper relies on 25 national surveys from 16 countries taken from waves 4 (years 1999–2004; 10 584 individuals), 5 (years 2005–2008; 8187 individuals), and 6 (2010–2014; 11 980 individuals) of the World Values Survey (WVS) database. We focus on the MENA region: Algeria, Bahrain, Egypt, Iraq, Iran, Jordan, Kuwait, Lebanon, Libya, Morocco, Palestine, Qatar, Saudi Arabia, Tunisia, Turkey, and Yemen. Since our dependent variables are economic outcomes, we confine our sample to people 25–55 years of age, as the prime working age according to one's life cycle, when the vast bulk of individuals' economic activity takes place; 30,751 individual-level observations are available overall. Full-time wage workers (32.97%) and housewives (32.62%) are the largest groups among men and women, respectively, followed by the self-employed (13.53%), part-time wage workers (10.08%), the unemployed (6.66%), the retired (2.55%), and students (1.57%).

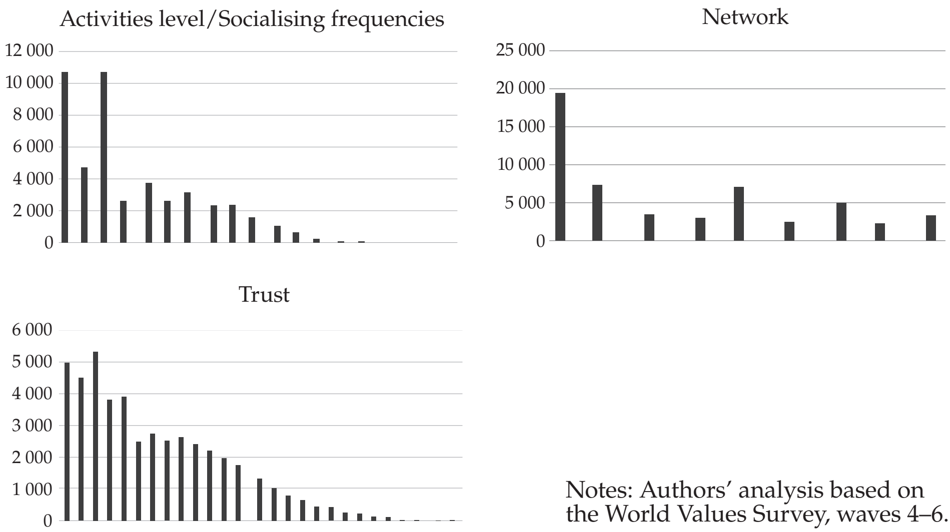
Results

The optimal number of clusters and their properties

Figure 1 reveals that the distribution of workers' social activity, the quality of their social networks, and their trust levels have 15, 9, and 23 distinct modes or groupings, respectively.

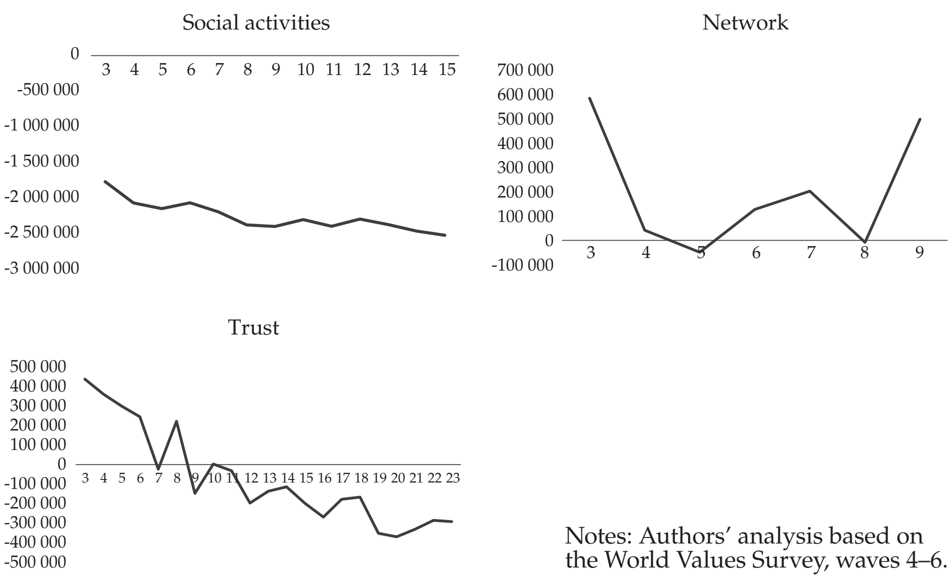
Figure 2 illustrates the Bayesian Information Criteria (BIC) corresponding to all the alternative counts of clusters for each social capital dimension. The optimal counts of clusters are found where BIC is minimised, that is, at 15 for the level of social activity (that is, the maximum number considered; BIC=–2 516 700), 5 for the quality of social networks (BIC=–49 002), and 20 for trust (BIC=–369 710), respectively. A reassuring feature in Figure 2 is that the BIC evolves in a consistent direction, near monotonically and at a diminishing rate for the level of social activity and trust, and approaches a U shape for the quality of social networks. This provides some validation for the selected count of clusters with respect to neighbouring values.

Figure 1. Distribution of each dimension of social capital



Notes: Authors' analysis based on the World Values Survey, waves 4–6.

Figure 2. Bayesian Information Criteria by the count of clusters



Notes: Authors' analysis based on the World Values Survey, waves 4–6.

Table 2. Representative (average) values of social capital dimensions, by country-group and gender

	Women			Men		
	Activity	Network	Trust	Activity	Network	Trust
Gulf Cooperation Council (GCC; Bahrain, Kuwait, Qatar, Saudi Arabia)	0.2681	1.0268	0.5740	0.3112	1.0794	0.5878
Middle-income (Algeria, Egypt, Iraq, Jordan, Lebanon, Libya, Morocco, Tunisia, Iran, Turkey)	0.1902	0.6211	0.4524	0.2593	0.5965	0.4255
Low-income and conflict-affected (Palestine, Yemen)	0.1172	1.3801	0.6936	0.2195	1.4704	0.5818

Table 3. Average probabilities of belonging to each social capital cluster, by country-group and gender

	Gulf Cooperation Council (GCC)						Middle-income						Low-income and conflict-affected					
Countries	Bahrain, Kuwait, Qatar, Saudi Arabia						Algeria, Egypt, Iraq, Jordan, Lebanon, Libya, Morocco, Tunisia, Iran, Turkey						Palestine, Yemen					
#	Women			Men			Women			Men			Women			Men		
Clusters	Activity	Network	Trust	Activity	Network	Trust	Activity	Network	Trust	Activity	Network	Trust	Activity	Network	Trust	Activity	Network	Trust
1	0.325	0.011	0.641	0.230	0.003	0.658	0.313	0.298	0.378	0.175	0.271	0.369	0.488	0.019	0.737	0.025	0.007	0.725
2	0.007	0.308	0.001	0.010	0.370	0.001	0.119	0.163	0.003	0.054	0.136	0.003	0.102	0.774	0.007	0.027	0.621	0.003
3	0.015	0.310	0.000	0.024	0.281	0.000	0.016	0.430	0.004	0.054	0.467	0.004	0.000	0.000	0.001	0.000	0.000	0.000
4	0.009	0.070	0.000	0.007	0.039	0.000	0.000	0.020	0.002	0.000	0.020	0.000	0.000	0.015	0.000	0.000	0.013	0.000
5	0.127	0.300	0.003	0.040	0.307	0.005	0.228	0.089	0.000	0.184	0.106	0.000	0.000	0.193	0.000	0.000	0.358	0.000
6	0.000		0.000	0.000		0.000	0.008		0.094	0.001		0.094	0.000		0.001	0.000		0.000
7	0.015		0.000	0.005		0.000	0.025		0.000	0.056		0.000	0.000		0.000	0.000		0.000
8	0.062		0.005	0.098		0.003	0.161		0.000	0.263		0.000	0.153		0.000	0.514		0.000
9	0.246		0.000	0.319		0.000	0.092		0.001	0.120		0.001	0.247		0.000	0.399		0.000
10	0.016		0.000	0.008		0.001	0.004		0.005	0.003		0.005	0.003		0.009	0.001		0.021
11	0.139		0.255	0.163		0.222	0.026		0.258	0.054		0.251	0.000		0.001	0.000		0.000
12	0.000		0.004	0.000		0.007	0.000		0.000	0.001		0.000	0.000		0.000	0.001		0.000
13	0.007		0.000	0.019		0.000	0.004		0.002	0.012		0.001	0.003		0.000	0.013		0.000
14	0.009		0.022	0.046		0.027	0.002		0.149	0.011		0.117	0.000		0.201	0.000		0.005
15	0.023		0.005	0.029		0.003	0.003		0.006	0.012		0.007	0.004		0.023	0.018		0.013
16			0.053			0.058			0.092			0.140			0.001			0.004
17			0.000			0.000			0.000			0.001			0.000			0.000
18			0.003			0.003			0.001			0.001			0.000			0.000
19			0.006			0.008			0.000			0.000			0.000			0.000
20			0.003			0.004			0.005			0.005			0.018			0.024

Table 2 presents the averages of the estimates of the values of social-capital dimensions by country group and gender. These are representative of the values used in the following regressions. Table 3 reports the estimated probabilities of women and men in each country group being assigned to each cluster.[3] The results show that the probabilities are similar between men and women within a group of countries (with some notable exceptions, such as activity levels between men and women in low-income countries) but differ across country groups. Figure 3 illustrates the joint distribution of the predicted values of the dimensions of social capital by gender (across all countries; disaggregation by country group is available on request), a pair of dimensions at a time. The results reveal that trust and social network are associated positively with each other in both gender groups, while the level of social activity is associated negatively with the other two dimensions of social capital. The distributions vary across country-groups, pointing to institutional, cultural, religious differences, but the differences between genders are minor – as we found in Table 3. This suggests that women and men in the MENA region have similar predispositions and opportunities for social engagement. This consistency in distributions allows us to assess the impact of social capital on women's and men's employment outcomes using the same framework and suggests that gender gaps in employment may not be due to differential patterns in social engagement. The differences across countries suggest that country income-group fixed effects should be used in regressions.

Instrumenting for social-capital clusters

Social capital may be endogenous to workers' employment outcomes, because workers in different occupations have different access to networking, capacity to socialise, and possibly even trust in their peers and surrounding institutions. This endogeneity can be addressed by isolating the part of social capital that is independent of employment outcomes – an instrumental variable approach. As an instrument for the potentially endogenous stock of social capital in employment regressions, a 'doughnut' IV is employed. This essentially distils the exogenous part of an individual's potentially endogenous social capital that is explained by

[3] Figures A1–A7 illustrate these results by gender and country income group. In Figure A1, a monotonic pattern is found in the level of social activity while other dimensions of social capital exhibit a U-shaped pattern for both men and women. Figure A2 also illustrates the results by country income group, showing interesting patterns in gender inequality for social capital: men generally report higher levels than women except for the quality of social networks in middle-income countries, and trust in middle-income and low-income economies. Such dissimilar patterns in the values of social capital dimensions imply that the three dimensions of social capital may not be very similar in nature, and in fact function quite differently depending on workers' gender and country of residence, or possibly other covariates.

social capital norms prevalent in the individual's larger community rather than the individual's own character or performance. The intuition behind a doughnut IV in this setting lies in the conceptual nature of social capital, that is, that a person's accumulation of social capital is influenced by their interaction with their community, and by the stock of social capital prevalent in the community. At the same time, the level of social capital prevalent among one's neighbours does not bias the employment effect of one's own social capital in the structural model (evaluated informally by adding the instruments to the structural equations along with non-instrumented social capital). Individuals' error terms are thus independent of the doughnut IV, but the IV has a significant partial effect on one's social capital (evaluated through simple correlations, and through the first stage regressions). Our IVs thus satisfy the second-stage exclusion and the first-stage significance conditions for valid IVs [Warner 2001; Flora 2004; Kawachi 2006; Ling and Dale 2013].

The community-level doughnut IV is defined exogenously for demographic cells at the level of countries, narrow age cohorts, the sizes of the towns of residence, and survey waves. For individuals in each demographic cell (excluding the individual in question), the averages of estimates for the three social-capital dimensions are obtained, and they are used as the doughnut IVs for the social-capital dimensions of the individual in question.

Probabilistic regressions of employment status

Using the instrumented values of individuals' social capital, we next run probabilistic regressions for model A (*employed vs non-employed*$_{it}$) and model B (*full-time wage vs part-time wage/self-employed*$_{it}$) to investigate the effect of a person's social capital on his/her propensity to hold employment or have full-time wage work. For women, the marginal probabilities of being employed and (once employed) of having a full-time position increase with the values of all dimensions of social capital. The probability of women accepting employment rises by 98% as their level of social activity increases by one category and rises by 109% as their trust level increases. Interestingly, men's results exhibit quite different patterns: the level of social activity has a negative effect on men's prospect of being employed, while their trust level affects it positively. The quality of one's network has surprisingly little effect on the employment outcomes of either gender.

In model B, we find generally adverse effects for most dimensions of social capital on workers' full-time status. In particular, women's probability of attaining a full-time job falls at higher levels of social activity and trust. Similarly, men's probability of holding a full-time job falls by two-thirds with an increase in their social activity, while it increases by 45% with an increase in their trust level. The quality of one's social networks turns out to be significant only among men: men's chances of obtaining a full-time job increase with the quality of their social

Table 4. Marginal probabilities for models A and B

	Model A (employed vs non-employedit)					
	Women (6329 observations)			Men (6760 observations)		
	Social activity	Network	Trust	Social activity	Network	Trust
Marginal probabilities	0.9796	0.0139	1.0899	–0.1277	–0.0326	0.2074
	(0.000)	(0.904)	(0.000)	(0.032)	(0.394)	(0.000)

	Model B (full-time wage vs part-time wage/self-employedit)					
	Women (2346 observations)			Men (6146 observations)		
Marginal probabilities	–0.7691	–0.2125	1.2825	–0.6866	0.1692	0.445
	(0.001)	(0.377)	(0.000)	(0.000)	(0.020)	(0.000)

Notes: Authors' analysis based on World Values Survey, waves 4–6; p-values in parentheses.

network, while for women it does not matter. The key numerical results of models A and B are summarised in Table 4. The units of social-capital indicators can be used to interpret the marginal probabilities. For example, a one-unit increase in social activity implies that a person is becoming more active (going from being a non-member to being an inactive member, or from being inactive to being active) in various social organisations or spending more time with friends or family (from practically never to a few times a year, or from a few times a year to weekly). Similarly, a one-unit increase in network implies getting information from friends or colleagues more often or recognising oneself as part of a community in a stronger sense. A one-unit increase in trust implies gaining more trust or confidence in one's family or neighbourhood, in the government or institutions in society, or even in the justice system/courts or in people of other religions.

Multinomial ordered-probability regressions: models C, D and E

Next we estimate the ordered-probability regressions for models C (degree of autonomy on a job), D (intellectual nature of a job), and E (routine to creative job) in order to investigate the effects of social capital on one's prospect of holding a certain quality of job. These models are estimated on restricted samples of full-time wage workers, and hence cover substantially fewer women, who are typically economically inactive or are second earners in their family [Singell and Lillydahl 1986; Winkler and Rose 2001; Morrisson and Jutting 2005; Kaygusuz 2010]. Specifically, these models cover 2285–2297 men, but only 893–896 women.

Table 5 presents the central results of these regressions, namely the marginal effects of the three dimensions of social capital (instrumented) on the probability of each employment outcome across the 1–10 spectrum of the dependent variables.[4] Table 5 and Figure 4 confirm that the marginal effects at the extreme values of 1 and 10 are estimated somewhat off the trends (or with less precision) seen between values 2 and 9.

The first block in Table 5 shows that the degree of autonomy that women enjoy in their jobs is associated negatively with their level of trust (borderline significant at the 10% level). Similarly, among men the degree of autonomy is associated negatively with their trust level, but there is a strong positive association with their level of social activity and networks. Some interpretations are that: (1) jobs with greater autonomy require staffing by workers who are inherently

[4] To fix our focus in Table 5, selected marginal effects – those on the values of 3 and 7 of the dependent variables – are highlighted as of particular interest, interpreted as the effects on relatively low and relatively high degrees of job autonomy (intellectuality or creativity, respectively), with adequate sample sizes each. By contrast, values 1–2 and 8–10 are for smaller groups of (outlying) workers and their marginal effects are estimated on smaller sample sizes.

active and who possess resources such as networks, but who have critical world-views and vantage points, including independent reasoning and a scepticism towards externally provided stimuli; and/or that (2) workers demonstrate their preferences in regard to relying on external factors by choosing appropriate jobs. Workers are thus matched to jobs based on their soft skills.

The second, middle block in Table 5 shows that, among both gender groups, the degree of cognitive load in one's job has a weakly negative association with one's level of social networks (near significant at the 10% level among women). Among men, it is also associated strongly positively with social activity, and strongly negatively with one's personal trust. As with job autonomy, the likely culprits have to do with employers' demands over workers' skill sets across different job types, and with workers' own self-selection into careers and jobs. Jobs and careers with a heavy cognitive load may attract – from the demand or supply side – workers with high levels of social activity but, perhaps incidentally, also workers with limited active social networks and low trust in social institutions – such as people with advanced independent reasoning and conservative views of external forces.

Finally, the bottom block in Table 5 shows that, among both men and women, the degree of creativity in a job is associated strongly positively with the activity level of incumbent workers' social engagement, but negatively with workers' social networks (and weakly negatively also with their level of trust in social institutions). In creative jobs, then, workers appear to be selected from among those with more outgoing socialising levels but narrower social networks.

Taken together, the results in Table 5 confirm that the three dimensions of social capital have heterogeneous effects on workers' employment status, the effects vary by gender, and the effects evolve near monotonically across the spectra of employment types. The marginal effects have, for the most part, the same signs between women and men (except in model D) but vary in magnitude and significance. While the effects on women's employment type are typically not significant statistically (partly on account of the smaller sample of women), and at most one social-capital dimension is significant in women's regressions, the effects of 2–3 social-capital dimensions are highly significant in men's regressions. For completeness, the models presented in Tables 4 and 5 are highly significant, as evidenced by their R-squared and Wald chi-square statistics.[5]

[5] The validity of the ordered probability models relies on the proportional odds (PO) assumption that the modeled effects are consistent across all outcomes. This property is confirmed to be reasonable conceptually, but an empirical Brant [1999] test puts the assumption in question. While some variables satisfying the PO assumption, the chi-square statistics for the set of all explanatory variables in models C, D and E reject the null hypothesis of validity, indicating that at least one variable violates the PO assumption for at least one outcome. This is not surprising given that the Brant test is not powerful

Discussion

The results of our analysis paint a varied picture of the role of social capital in explaining workers' employment outcomes and types of jobs. We found that workers' trust in social institutions, the way it was defined here, is conducive to workers' more active roles in the labour market in terms of the prospect of employment and full-time work but appears to be a detractor (or a predictor of non-selection) from autonomous, intellectual, and creative positions. The level of workers' social networks is not a significant predictor of their labour-market activity, and only appears to matter (positively) for men's selection to autonomous posts and to non-creative/routine posts. Surprisingly, a higher level of social activity is broadly associated negatively with employment and full-time work, but positively with the prospect of selection to autonomous, intellectual, and creative jobs.

It is worth repeating that the role of the dimensions of social capital differs by gender in relation to how intellectual a job is, but not in relation to how autonomous and creative it is. (The top and bottom blocks in Table 5 show the marginal effects of the same sign between women and men, but not in the middle block. Figure 4 shows this visually between columns 1 and 3, but not 2.) One can infer that men and women face different selection processes (self-selection and/or employer selection) for jobs at the high and low ends of the spectrum of how intellectual a job is. While the level of social activity and trust have a bearing on the prospect of men being matched to jobs, for women it is only their social network that correlates with job selection. An example could be that *wasta* networks play a disproportionally high role in women's selection to less intellectual jobs (no effect among men in relation to the intellectual load of jobs), while the levels of social activity and trust help predict men's selection/non-selection to jobs at the high and low ends of the intellectual-load spectrum of job types.

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and is 'anticonservative' [Peterson and Harrell 1990; O'Connell 2006]. The test nearly always yields small p-values, particularly when the number of explanatory variables is large [Brant 1990], the sample size is large [Clogg and Shihadeh 1994], or the covariates include continuous variables [Allison 1999]. In case of rejection of the null hypothesis, the *generalised ordinal regression model*, allowing dissimilar effects by outcome, may provide a more consistent and closer fit to the data in question [Grace-Martin 2020], but it has the disadvantage that it is more parameterised, possibly less efficient, and more cumbersome to interpret when we are interested in general trends across all outcome values. An alternative solution would be a series of binary probit/logistic regressions if the interest is in marginal effects at a specific outcome value. In this context, we interpret the Brant test results as prescribing that the estimated effects be interpreted as the *general trend* in the true effects across outcomes of the response variables, rather than as the specific marginal effects at any outcome value. For completeness, the ordered probability models were also estimated with fewer outcome categories – 3 or 5 instead of 10 – but the results of the Brant tests remain unchanged. This helps to validate the robustness of our main models.

Table 5. Marginal probabilities for models C, D and E – first part

Level of job characteristic	Model C (degree of autonomy, 1 to 10)					
	Women (893 observations)			Men (2285 observations)		
	Social activity	Network	Trust	Social activity	Network	Trust
1	–.063 (.677)	–.312 (.521)	.158 (.103)	–.213 (.022)	–.172 (.000)	.093 (.150)
2	–.017 (.676)	–.082 (.524)	.042 (.109)	–.074 (.025)	–.060 (.001)	.032 (.155)
3	*–.017 (.676)*	*–.082 (.523)*	*.042 (.113)*	*–.081 (.024)*	*–.066 (.001)*	*.035 (.153)*
4	–.020 (.676)	–.101 (.525)	.051 (.115)	–.063 (.023)	–.051 (.001)	.027 (.154)
5	–.018 (.675)	–.090 (.527)	.045 (.114)	–.079 (.023)	–.064 (.001)	.034 (.154)
6	–.003 (.680)	–.015 (.554)	.008 (.219)	–.011 (.054)	–.009 (.021)	.005 (.194)
7	*.006 (.678)*	*.029 (.521)*	*–.015 (.119)*	*.027 (.031)*	*.022 (.001)*	*–.012 (.158)*
8	.017 (.676)	.083 (.522)	–.042 (.107)	.076 (.024)	.062 (.000)	–.033 (.152)
9	.017 (.677)	.085 (.522)	–.043 (.110)	.085 (.024)	.068 (.000)	–.037 (.154)
10	.098 (.676)	.484 (.523)	–.244 (.106)	.332 (.021)	.269 (.000)	–.145 (.151)

Table 5. Marginal probabilities for models C, D and E – second part

	Model D (manual to intellectual, 1 to 10)					
	Women (896 observations)			Men (2297 observations)		
	Social activity	Network	Trust	Social activity	Network	Trust
1	.023 (.895)	.837 (.157)	.003 (.982)	–.614 (.000)	.058 (.472)	.251 (.002)
2	*.005 (.895)*	*.159 (.161)*	*.001 (.982)*	*–.107 (.000)*	*.010 (.470)*	*.044 (.021)*
3	.005 (.895)	.178 (.159)	.001 (.982)	–.074 (.000)	.007 (.470)	.030 (.022)
4	.003 (.895)	.112 (.160)	.000 (.982)	–.034 (.000)	.003 (.470)	.014 (.026)
5	.004 (.895)	.127 (.156)	.000 (.982)	–.016 (.029)	.002 (.048)	.007 (.105)
6	.000 (.913)	.002 (.833)	.000 (.982)	.039 (.000)	–.004 (.477)	–.016 (.020)
7	*–.002 (.895)*	*–.056 (.195)*	*–.000 (.982)*	*.083 (.000)*	*–.008 (.474)*	*–.034 (.019)*
8	–.005 (.895)	–.164 (.168)	–.001 (.982)	.144 (.000)	–.014 (.473)	–.059 (.019)
9	–.004 (.895)	–.137 (.168)	–.000 (.982)	.148 (.000)	–.014 (.472)	–.061 (.021)
10	–.030 (.895)	–1.054 (.150)	–.003 (.982)	.431 (.000)	–.041 (.469)	–.176 (.020)

Table 5. Marginal probabilities for models C, D and E – third part

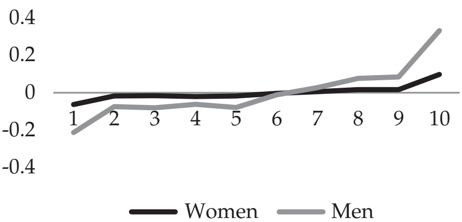
	Model E (routine to creative, 1 to 10)					
	Women (896 observations)			Men (2295 observations)		
	Social activity	Network	Trust	Social activity	Network	Trust
1	–.857 (.004)	1.816 (.008)	.237 (.177)	–.665 (.000)	.357 (.000)	.086 (.460)
2	–.091 (.006)	.193 (.009)	.025 (.183)	–.111 (.000)	.060 (.000)	.014 (.462)
3	*–.056 (.007)*	*.118 (.094)*	*.015 (.192)*	*–.069 (.000)*	*.037 (.000)*	*.009 (.463)*
4	–.009 (.217)	.019 (.277)	.003 (.359)	–.018 (.004)	.010 (.004)	.002 (.474)
5	.062 (.017)	–.131 (.114)	–.017 (.190)	.047 (.001)	–.025 (.002)	–.006 (.460)
6	.087 (.009)	–.185 (.096)	–.024 (.179)	.073 (.000)	–.039 (.000)	–.010 (.460)
7	*.172 (.006)*	*–.365 (.009)*	*–.048 (.180)*	*.128 (.000)*	*–.068 (.000)*	*–.017 (.460)*
8	.184 (.006)	–.390 (.009)	–.051 (.182)	.165 (.000)	–.088 (.000)	–.021 (.461)
9	.138 (.007)	–.217 (.100)	–.038 (.178)	.149 (.000)	–.080 (.000)	–.019 (.461)
10	.370 (.004)	–.784 (.079)	–.102 (.186)	.303 (.000)	–.162 (.000)	–.039 (.462)

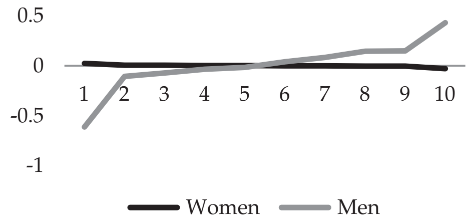
Notes: Authors' analysis based on the World Values Survey, waves 4–6. Values shown are the marginal effects of a one–cluster increase in the dimension of social capital. P–values are in parentheses, the marginal effects on values 3 and 7 are in italics, for ease of reference to the values of interest (representing moderately low and moderately high degrees of autonomy/cognitive load/creativity).

Figure 3. Summary of marginal effects on employment types by social-capital dimension – first part

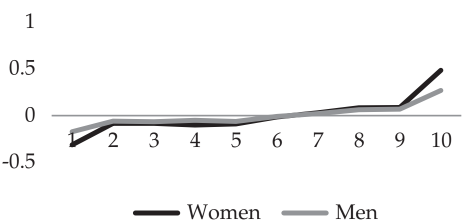
Model C: Job autonomy (1–10) | Model D: Job cognitive load (1–10)

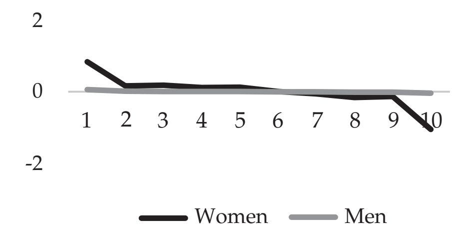
Level of social activity



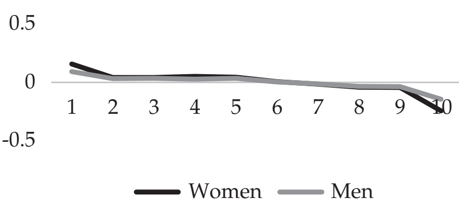


Quality of social networks





Trust in social institutions



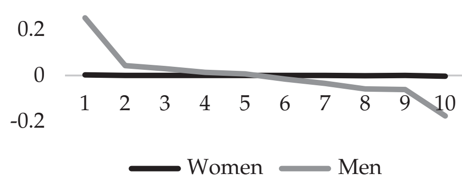
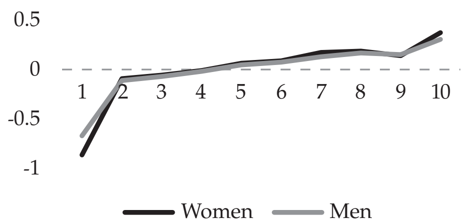


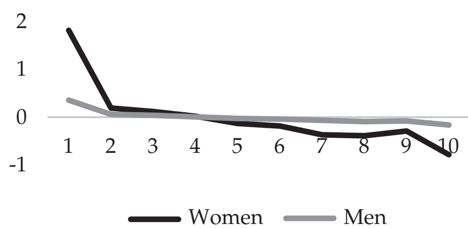
Figure 3. Summary of marginal effects on employment types by social-capital dimension – second part

Model E: Job creativity (1–10)

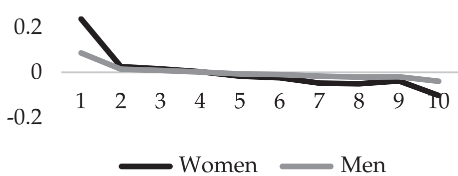
Level of social activity



Quality of social networks



Trust in social institutions



Notes: Authors' analysis based on the World Values Survey, waves 4–6. The values shown are the marginal effects of a one-cluster increase in the dimension of social capital on the probability of a specific job type.

Social capital acquisition and employment-type prospects

One implication of the varied effects of the dimensions of social capital is that observing workers' social-capital profiles would go some way to predicting their employment status and job type – at present or in the future. Taking this line of thought one step further, and interpreting the findings causally, we could attempt to provide advice on what other skills complementary to the existing profiles of social capital should be invested in by job candidates that would endow them with a similar skill set to that of current incumbents in a given job type. Table 6 summarises the empirically observed associations between the dimensions of social capital and workers' employment status: '+' ('0' or '–') indicates that the dimension of social capital is associated positively (or not clearly or negatively, respectively) with a particular employment type.

Policy implications

The analysis and findings in this study contribute to filling important voids in existing scholarship and policy discourse on the role of workers' social capital in MENA countries' labour markets – and by extension the labour markets in developing countries worldwide. By surveying the region's literature on social capital, we also aimed to increase global awareness of the economic reality in the region's labour markets. Given what we know and what we have confirmed, policymakers across the region would be advised to harness the value of their citizens' social capital for achieving certain common goals, such as efficient matching of workers and jobs, better fluidity in labour relations, efficient labour mobility across various sectors of the countries' labour markets, and enhanced social trust and solidarity.

Our findings suggest that workers' incentives for human/social capital acquisition are linked to their career expectations. Failures to harness workers' social capital affect workers' personal outcomes and act as a burden on the region's economic and social potential. The MENA region's notoriously precarious labour market conditions and the fractionalisation of the civic sphere – and, by extension, civic discontent – go hand in hand with the failures to account for workers' social aptitudes and needs. The plight of mismatched, underutilised, and disenfranchised workers calls for urgent action to empower them to make use of all their endowments, in order to enable them to transition to decent jobs and fitting civic roles. The gaps are all the more salient given that the MENA countries' aspirations under the Fourth Industrial Revolution depend crucially on the formation of human capital, networks, sharing, and trust. We hope that our findings will contribute to a policy discourse on the appropriate facilitation of social engagement, networks, and trust among the region's workforce towards the fulfilment of the countries' development strategies.

Table 6. Social capital and employment-type associations

		Social activity		Social network		Trust in social institutions	
Model	Employment type	Women	Men	Women	Men	Women	Men
A	Employed	+	–	0	0	+	+
B	Full-time	–	–	0	+	+	+
C	Non-autonomous	0	–	0	–	+	+
	Autonomous	0	+	0	+	–	–
D	Manual	0	–	0	0	0	+
	Intellectual	0	+	0	0	0	–
E	Routine	–	–	+	+	+	0
	Creative	+	+	–	–	–	0

Notes: Authors' analysis based on the World Values Survey, waves 4–6. The values are a function of the individual and joint significance of the corresponding marginal effects. In models C–E, marginal effects at values 3 and 7 are considered; +/0/–: the dimension of social capital is associated positively/not clearly/negatively with the corresponding employment type.

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