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Multidimensional Deprivation from Labor Market Opportunities in Armenia: Evidence from 2018 and 2020

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Abstract
This paper explores the multidimensional deprivation from labor market opportunities in Armenia by constructing a Quality of Employment measure. Using Labor Force Survey datasets for the years 2018 and 2020, we conduct a comparative analysis for a group of job-separated individuals. The identified dimensions of deprivation from labor market opportunities prior to and after the onset of COVID-19 are *reasons for separating from a job*, *reasons for not looking for a job*, and *main obstacles in finding a job*. These dimensions enable to study employee-level (*supply factors*) and job-related characteristics (*demand factors*). Our study shows that demand factors are the primary drivers of amplified deprivation in times of the pandemic. Also, we observe that the gender gap in the labor market deprivation has been increased during the pandemic, further amplified for married women. Interestingly, gender gap in deprivation is invariant to the occupational composition.

Keywords Multidimensional deprivation · Quality of employment · Labor market · COVID-19 · Gender gap · Armenia

JEL Classification J01 · J08 · O18 · H12

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Introduction

Uncertainties and economic shocks, such as COVID-19, hit significantly labor markets. The International Labour Organization (ILO) reports about 25 million job losses after the COVID-19 pandemic breakout (ILO 2020).Studies conducted immediately after the onset of COVID-19 suggest that lockdown and social distancing measures that many countries introduced to curb the spread of the pandemic had a large impact on employment (Brodeur et al. 2020; Coibion et al. 2020). Quality of working life is a multidimensional and can capture the development of a labor market beyond the simple consideration of the quantity of jobs generated. Given the multifaceted aspect of the job quality, a multidimensional measure of quality of employment (QoE) is constructed for cross-country studies (Gonzalez et al. 2021; Sehnbruch et al. 2020) and for single countries (Huneeus et al. 2015; Gómez-Salcedo et al. 2017).

In this paper we explore labor market changes in Armenia during the COVID-19 shock. In particular, we analyze the deprivation from labor market outcomes[1] in pre- and post-COVID-19 periods for individuals separated from a job. We examine a set of labor market related dimensions, such as *reasons for job separation* and *for not looking for a job*, *obstacles in finding a job,* and individual characteristics, such as *education, vocational education/ training and occupation match*. Furthermore, we capture the heterogeneity of deprivations by individuals' gender, age, marital status, rural-urban locations, as well as occupation types. We use the 2018 and 2020 Labor Force Surveys (LFS) collected by the National Statistical Service of the Republic of Armenia (NSSRA). To assess changes in labor market opportunities, we apply Alkire-Foster dual cut-off methodology (Alkire and Foster 2011) commonly used in multidimensional poverty studies (Alkire et al. 2021; Burchi et al. 2022; Pham et al. 2020).

The multidimensional measure of the QoE is relatively new in the literature, and there are continuous efforts in identifying its necessary dimensions and minimum standards (Sehnbruch et al. 2020). Recent studies exploring the multidimensional deprivation from labor market consider dimensions of income, employment stability, security and conditions (Gonzalez et al. 2021; Sehnbruch et al. 2020). Our paper therefore contributes to the existing knowledge by incorporating a set of job search related dimensions as well as employee level characteristics (such as education, occupation match) in the multidimensional measure of QoE. Many instances of job separation follow paths that are not comprehensively described in existing models, and further research is needed to shed light on what drives deprivation of the unemployed population (Lee and Mitchell 1994; Maertz and Campion 2004Steel, 2002). In this context, the factors that we include in our analysis on job-separated individuals allow us to elaborate on occupational mobility, that is to say the job-to-joblessness transition of individuals separated from jobs. We built on the academic research that measures selected employment conditions that are conducive to QoE

[1] In our study, we use opportunities and outcomes interchangeably.

(Gonzalez et al. 2021; Olsen and Kalleberg 2004; Sehnbruch et al. 2020). In particular, we adjust the framework of Gonzalez et al. (2021) and focus on deprivation factors of individuals separated from jobs.

The Armenian labor market is an interesting case for this exploration as the analysis of the LFS for the period 2014–2020 indicates we that although the job separation rate was the highest in 2020, many of job-separated individuals were not eager to look for new jobs. In Armenia, the NSSRA (2020) reports that in the first nine months of 2020, approximately 47,000 people lost their employment and stable income. The official statistics state that unemployment increased from 17.7 percent to about 20 percent in this period. Among the laid-off employees only 17 percent continued actively seeking a job; about 60 percent had given up on their job search. These people or their families either had a high intention to emigrate or had already become receivers of a social protection pension. In this light, it is important to consider complementing the conventional employment measures with insights from the multidimensional measure of employment deprivation in order to provide solid basis for evidence-driven policymaking.[2]

Furthermore, we consider a period that enables us to assess changes in labor market opportunities translated into deprivations in the year of the major external shock, COVID-19. Understanding the predictors of job separation, as well as changes in labor market conditions in times of unprecedented events can be an important input for policy makers and organization managers. While there is voluminous literature from high-income countries exploring labor market conditions during the COVID-19 (Adams-Prassl et al 2020; Crossley et al 2021; Chetty et al. 2020), such evidence from the developing world is scant, largely due to lack of data. Studies on developing countries mostly rely on survey evidence that is collected for the specific purpose of studying the crisis and addresses specific questions (for instance, Bundervoet et al. 2022).

Job separation is one of the key determinants of unemployment (Barnichon 2012). Job separation probabilities refer to both voluntary turnover and involuntary dismissals (Zavodny 2003). Over the last decade, the literature on job separation has focused on the predictors and antecedents of turnover (Holtom et al. 2008; Griffeth and Hom 2001). A large portion of this research examines the antecedents of quitting, primarily focusing on process research that addresses how people quit (Kulik et al. 2012), and on content research which explores motivations of quit (Griffeth et al. 2000). Some of the recent studies take into consideration employees' reported reasons for leaving (Maertz et al. 2003; Westaby 2005). In this context, job separation and labor market studies are increasingly using a multidimensional measure of QoE (Alaimo et al., 2020; Gonzalez et al. 2021; Sehnbruch et al. 2020). QoE posits that simply having a job is not sufficient for ensuring the wellbeing of an employee (or any dependents in the household). To achieve minimum levels of functioning in dimensions related to the wellbeing, job stability, security, wage and other

[2] A multidimensional measure of the QoE is a complementary indicator to the traditional labor market indicators (such as the employment rate) and contributes to the UN Sustainable Development Goals (SDGs) in achieving ‘‘Decent Work for All" (UN 2015).

dimensions should be taken into consideration. This argumentation builds on Sen (2006) who considers that deprivation does not belong only to monetary (income) but also to non-monetary (such as health, education, benefits) dimensions. This means that unemployment (including job separation) is interpreted as a failure of certain basic capabilities. This is an important aspect, since the COVID-19 pandemic had disparate effects on different groups of population, mostly explained by the kind of job a person holds, household and family structure, geographic location, and various measures of socio-economic status (Tverdostup 2022; Aum et al. 2021; Montenovo, et al. 2020).

The key finding from the deprivation analysis is that there are significant changes at the extensive margin in terms of the increased proportion of deprived individuals in 2020 compared to 2018. In the meantime, we do not observe shifts at the intensive margin in terms of the average deprivation intensity changes. Regression results bring novel insights on labor market deprivation effects for women. In particular, deprivation is higher for married women during the pandemic. This result does not depend on the occupational composition among women. Our research shapes a unique study for Armenia, as there is no prior academic study exploring the Armenian labor market conditions during the COVID-19 pandemic. While there are several descriptive reports on the Armenian labor market, such as the NSSRA annual reports, the study by ILO on Armenia (ILO 2020), and the World Bank report on Labor Market Dynamics (WB 2007), they remain at a descriptive level. Our study is the first attempt to explore the deprivation from labor market opportunities in Armenia based on country-level representative data. Our contribution is also to embed the long-lasting structural problems in the labor market, such as gender-based wage gap, informal employment, while examining the deprivation in times of the COVID-19.

The remainder of the article is organized as follows. Part two provides a literature review. Part three describes the labor market trends in Armenia. Part four develops the method and the data. Multidimensional deprivation analysis is presented in part five. Regression analysis is developed in part six. Part seven concludes the study.

Literature Review

An increasing number of studies explore heterogeneous consequences of the COVID-19 shock on individuals and labor markets (Kikuchi et al. 2021; Acemoglu et al. 2020; Alon et al. 2020a, just to name a few). Evidence from developed countries underline the negative consequences of the COVID-19 on the labor market (Huang et al. (2020) for the US; Kikuchi et al. (2021) for Japan). Predominantly, the studies conducted after the COVID-19 outbreak corroborate the findings of the pre-COVID economic literature on the labor market.

Existent evidence suggests that earning losses from job separation are highly persistent (Stevens 1997) and much more severe when they occur in recessions (Davis and von Wachter 2011). The job-to-joblessness transition of individuals separating from jobs can affect the wellbeing of individuals by entailing disproportionate effects on certain groups of society and by making them deprived from a number of opportunities (education, health, income and others). As a result, labor market participants and potential entrants into the job market might become deprived from employment opportunities. The consequences of shocks are likely to carry on for a while and engender a chain reaction. The existing literature underlines the absence of a coherent theoretical framework for understanding and measuring QoE and deploys the concepts related to job quality that have evolved over time (Burchell et al. 2014; Sehnbruch et al. 2015; Piasna et al. 2019).

Next, we discuss in more details the key labor market aspects that can play a role in deprivation for individuals separated from jobs.

Job separation triggers: Job quitting is conditioned by independent effects of structural, procedural, and employee variables (Elvira and Zatzick 2002). In the economic literature, evidence postulates that there are many different paths to job separation, including more situational triggers (e. g., shocks) and different types of leaving (Hom et al. 2012). There are many reasons for job separation and those can be classified into "push" factors (such as industry needs), and "pull" factors (such as job opportunities or unexpected offers) (Maertz and Campion 2004; Zavodny 2003; Gunderson and Hotchkiss, 2007).

External factors condition job needs and may become push factors for job separation. This may be triggered by job-related shocks, such as downsizing (Lee et al. 1999), technological development (Zavodny 2003), management problems (Bjorn et al. 2016; Campion 1991) and others (Augner 2015). Another important external factor that can play a role in the labor supply is related to the shutdown of child-care, schooling, home, and family health care services (Dingel and Neiman 2020). Given those constraints the workforce in question may reduce the labor supply.

Alongside with external factors it is important to consider personal motivations in the light of dynamic aspects of job-separation decision complexity (Morrell and Arnold 2007). Personal factors, considered as determinants of quitting, include personal health, work stress, and family demand (Augner 2015; Levy-Garboua et al. 2007; Maertz and Kmitta 2012). Empirical evidence on the determinants of job separation (or quit) behavior shows that a person's current wage and alternative income plan are important factors (Morrell and Arnold 2007; Sicherman 1996). Other pull factors are related to job satisfaction, as well as to the fact of having dependents (Locke et al. 1976; Price 1989). Employees who are dissatisfied with their excessive load are most likely to quit. On the other hand, employees with dependents are less likely to quit.

Job-search behavior: The next group of variables we explore relates to the reasons of not searching for a job. Existing studies examine the predictors of job search behavior in samples of unemployed people (Kulik 2000; Lay and Brokenshire 1997; Wanberg 1997; Wanberg et al. 2002). Job-search behavior is complex and depends on supply factors (related to the individual's personal situation and abilities), as well as on demand factors (resources and opportunities outside an individual's personal control). Job-search constraint predictors are situational factors that might limit or restrict an individual's job-search efforts.

Type of employment can condition the job-search motivation. Even though nonstandard work arrangements (including seasonal employment) provide more flexibility, they are associated with an increased separation from a job (Grimshaw et al. 2001; Mourdoukoutas 1988). This can be due to the fact that such arrangements have worse job security, pay and fringe benefits as compared to those under regular (full-time) employment (Kalleberg et al. 2000; Rogers 1995). Personal factors that condition the job-search behavior include job-seeker human capital, reemployment constraints (e.g., lacking transportation, child-care, family responsibilities or illness), job seekers' economic need for work, and employer discrimination (Wanberg et al. 2002; Brooks and Buckner 1996).

Obstacles in finding a job: Evidence shows that job search competencies (characteristics that individuals need to perform well in a job setting) of unemployed individuals can play a role in the success of job-search process (Wanberg et al. 1999). Discrimination and incivility in job search are considered to hinder the job-finding process (Wanberg et al. 2020).

Education: Education level is an effective tool to reduce unemployment (Nunez and Livanos 2010). Evidence from developing economies suggests that the COVID-19 unequal impact on the labor market is due to workers' education and skills (Tverdostup 2022; Dasgupta and Murali 2020; Montenovo et al. 2020).

Vocational education/ training: It is documented that the quality of employment is associated with vocational training and skill development that help to improve employment practices and policies (Körner et al. 2012; Sehnbruch et al. 2015). Seniority and investment made in professional development (e.g., trainings) enhance employment quality (Becker 2009; Parsons 1972). For instance, people without qualifications are much more vulnerable to losing a job and are more prone to be locked in an unemployment trap than those with higher qualification levels (Giddens 2001).

Occupation (mis)match: Deprivation from the labor market can become costlier when coupled with increasing labor mismatch. Geographical space (urban versus rural areas) can be decisive in terms of employment opportunities, because unemployment is rooted in deeper structural factors, such as poor infrastructure, dysfunctional industries of a region (on the demand side) as well as a surplus of non-qualified or highly specialized labor (on the supply side).

Provided that job loss during a recession has durable and negative effects on future earnings and job security (Davis and von Wachter 2011), consequences of a crisis may persist and contribute to the deprivation of vulnerable groups for years to come. Thus, exploring triggers of deprivation in the pre- and post-COVID-19 periods among job-separated individuals is of high importance.

Background Information

Armenia is a developing country with around three million population located in Eastern Europe. After the collapse of the Soviet Union, Armenia declared its independence in 1991 and had to face numerous adverse shocks resulting in rather low resilience and absorption capability. The country experienced high rates of emigration and remittance inflows. Currently, the Armenian economy depends heavily on remittances, and a significant part of its population is below the national poverty line. According to the NSSRA (2021), the poverty rate estimate for 2020 is

27 percent, which is 0.6 percentage point higher than that in 2019, calculated with respect to the average poverty line.[3]

In response to the COVID-19, businesses in Armenia have undergone major changes. After the COVID-19 outbreak in Armenia in mid-March 2020, the Government has brought forward a need for amendments in the Labor Code to accommodate legally several restructuring processes. Some of those amendments create enabling conditions for female workers (e.g., child-care needs).

In Figs. 1a–c. We report job market related statistics from the Armenian LFS for the period 2014–2020. In Fig. 1a, the proportion of job seekers separated from a job throughout the last year in the labor force is compared to the proportion of job seekers (in the labor force) separated from a job in the current year. In general, the second proportion category has a decreasing tendency, but the drop in 2020 is substantially larger. The drop is also considerable for the proportion of job seekers in 2020 compared to that of 2019. From Fig. 1b, we observe that the two proportions of job seekers among separated are the lowest in 2020.

Finally, from Fig. 1c we observe that the proportions of individuals separated from a job during the last year and in the current year are the highest in 2020. Positive differences are even larger when we drop those individuals who separated from their last job more than one year ago.

Summarizing these observations, we conclude that while the job separation rate was the highest in 2020, many job-separated individuals were not eager to look for a new job. In our study, we particularly focus on reasons triggering this behavior in the first year of the pandemic compared to those in 2018. While the proportion of job seekers was the lowest in 2020 (Fig. 1a), it does not provide the full picture on the labor market and remains silent about difficulties that job-separated individuals faced during the pandemic.

Method and Data

We develop measures for multidimensional deprivation from labor market outcomes based on the Alkire-Foster methodology (Alkire and Foster 2011). This methodology proposes multidimensional poverty measures using a dual cut-off approach. The method is applied in several research areas, such as energy poverty (Ozughalu and Ogwumike 2019) and child-care (Kim 2019). The method has also been applied in labor market studies exploring the quality of employment (Gonzalez et al. 2021; Sehnbruch et al. 2020). Garcia-Perez et al. (2017) use the multidimensional approach to measure precarious employment. Similar to Gonzalez et al. (2021), we claim that the Alkire-Foster methodology is preferable over alternative methods such as partially ordered set methodology (e.g., Annoni and Bruggemann 2009), as it is widely used by policy makers and experts and can be easily associated with the measurements of multidimensional poverty.

[3] Average poverty line is AMD 44,482 (USD 91.0) per adult equivalent per month.

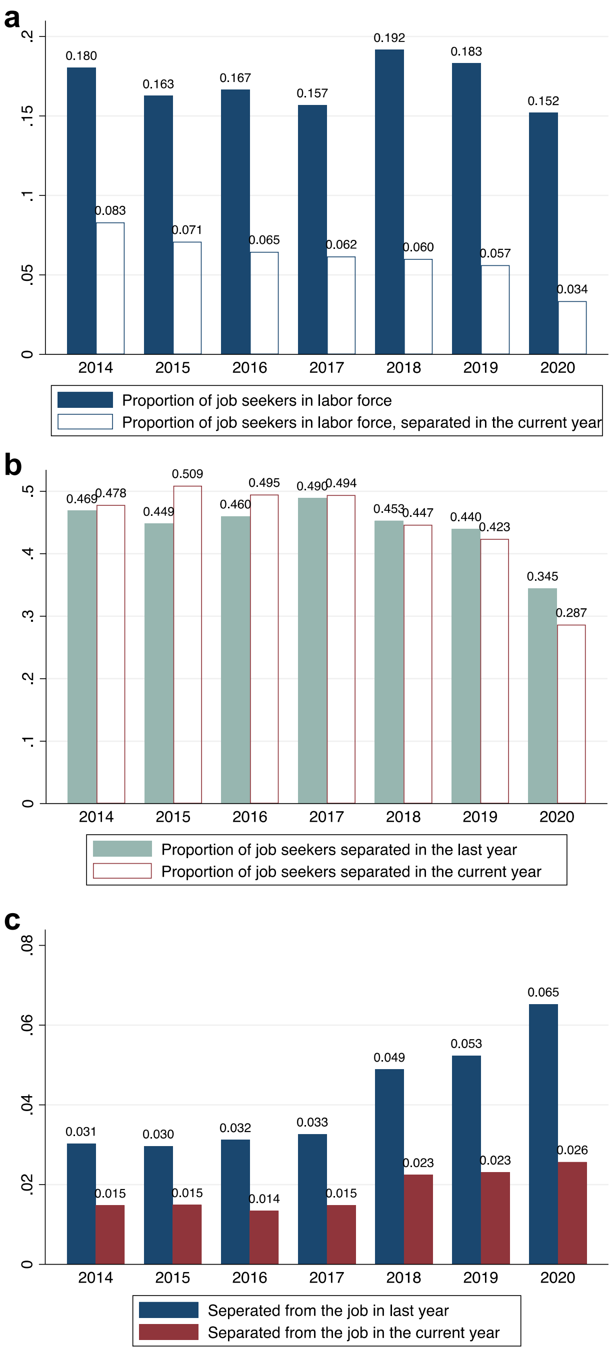

Fig. 1 **a** Proportion of job seekers. **b** Proportion of job seekers among separated from a job **c** Proportion of job-separated individuals in the labor force. *Note*: Authors' calculations based on LFS 2014–2020 datasets

In our study, the multidimensional deprivation indexes, namely, *headcount ratio*, *adjusted headcount ratio* and *average intensity of deprivation*, are constructed for the years 2018 and 2020, using Labor Force Survey datasets. As the method is quite extensively used in the literature, for the sake of brevity we unfold it in Appendix A.

Our comparative analysis consists of two parts. We compare deprivation indexes and contributions in the two datasets (2018 and 2020) and make judgements on labor market conditions and changes during the COVID-19. We take 2018 as a comparison base since economic growth expectations have become more rigorous after the "Velvet Revolution" and the formation of a new government in the spring of 2018 in Armenia. From the contribution analysis, we identify those indicators which capture the deprivation from labor market opportunities the most. Mapping from distinct indicators to the overall deprivation score in terms of absolute magnitudes and relative contributions is identified. We conduct this analysis for individuals who separated from a job (i) throughout the year prior to an interview week and (ii) throughout the current year of an interview. In the second case, we particularly observe individuals who separated from a job starting from January 2020, and therefore are more likely to be hit by the labor market effects of the pandemic.

We also conduct regression analysis to explore individual (age, gender, marital status), occupational and regional net effects on the deprivation score. We use occupation types based on International standard classification of occupations (ISCO)[4] to capture occupational differences. Regional disproportionalities in labor market performance are controlled for urban-rural areas. First, we estimate the regression model for the same subsamples used in the deprivation analysis. Then, we pool observations from 2018 and 2020 together and estimate specifications with interactions by exploring changes in gender gap in labor market deprivation and the compositional effect of occupation on it.

Dimensions and Indicators

In Table 1 we list dimensions and indicators, which are used for constructing multidimensional measurements: *reasons for separating from a job (1), reasons for not looking for a job (2), main obstacles in finding a job (3), education level (4), vocational education/ training (5) and occupation match (6).* Those stand as distinct dimensions, represented by one or more indicators. All individuals in the pool had been separated from a job during the year prior to the interview week. Some of them did not search for a job while others did. Respondents answering the questions corresponding to dimension 2 (reasons for not looking for a job) did not search for a new job. Respondents answering the questions related to dimension 3 were in the process of a job search.

[4] ISCO is an international classification by the International Labour Organization (ILO) for organizing jobs into a clearly defined set of groups according to the tasks and duties undertaken in the job. According to this classification, there are nine occupations: *legislators / senior officials / managers* (1), *professionals* (2); *technician professionals* (3); *clerks* (4); *service & sales workers* (5); *agricultural workers* (6), *craft workers* (7); *operators and assemblers* (8); and *elementary occupations* (9).

Table 1 Dimensions and indicators

Dimension	Indicator		Deprived if, …	Weight structure	
				Dim.	Ind.
1. Reasons for separating from a job	1	Demand factors	The reason is <u>either</u> of the following: Staff reduction / dissolution of the organization / lack of client/ customer / temporary lay-off End of a temporary / seasonal / one-time job Low wages	1/6	1/12
	2	Supply factors	The reason is <u>either</u> of the following: Illness / disability / care of a sick family member Household chores / family circumstances		1/12
2. Reasons for not looking for a job	3	Demand factors	The reason is either of the following: Waiting for the work/work season to resume Considered too young / too old to find a job Lack of jobs in the area	1/6	1/12
	4	Supply factors	The reason is <u>either</u> of the following: Household chores/family circumstances Illness/injury/incident Child care		1/12
3. Main obstacle in finding a job (launching your own business)	5	Demand factors	The reason is either of the following: Lack/absence of workplaces Low wage/income Considered too young/too old Being male/female Inclination for discrimination (disability/religion/appearance / family status)	1/6	1/12
	6	Supply factors	The reason is <u>either</u> of the following: Lack/absence of workplaces corresponding to an occupation/qualification Not enough work experience Lack of knowledge in languages/IT (computer, internet, etc.) Lack of job-search competencies[a]		1/12

Table 1 (continued)

Dimension	Indicator		Deprived if, …	Weight structure	
				Dim.	Ind.
4. Education level	7	Education (levels)	Less than secondary	1/6	1/6
5. Vocational education/training	8	Did you take any course, practice, private courses, vocational/ training, regular or occasional lasting even a few hours or days during the month (including the surveyed week)?	None of the courses in the list	1/6	1/6
6. Occupation match	9	Do you think your occupation (both formal and informal) is useful in your job/ in finding a job?	Not useful Do not have occupation Do not know/difficult to answer	1/6	1/6

[a]This indicator is captured by the lack of knowledge related to where and how to look for a job

The three dimensions, namely, reasons for separating from a job, reasons for not looking for a job and main obstacles in finding a job, constitute indicators grouped in demand and supply factors. Staff reduction or dissolution of an organization can be the basis for job separation, particularly relevant in times of the pandemic. It is documented in the literature that management and operational issues of companies can act as push factors for job separation (Bjorn et al. 2016; Augner 2015; Zavodny 2003). End of temporary/seasonal/one-time job are the second set of reasons for job separation. Considered too young/too old to find a job are common demand factors for dimensions 2 and 3. Discriminatory factors dominate in dimension 3. Supply factors refer to sources of deprivation inherent to a person. Factors such as illness/disability/care of sick family member and household chores are common determinants of job separation (dimension 2) or the main obstacle to find a job (dimension 3). Knowledge-based supply factors dominate in dimension 3.

Immediate or short-term changes under uncertainty are likely to be captured by the first three dimensions. Dimensions 4-6 need not be sensitive to the occurrence of an unexpected shock, such as the COVID-19 pandemic. We include these dimensions to capture even small differences in an education level, moderate or large differences in vocational education/ training (likely to occur in the fast-changing labor markets), and occupation match which can be directly linked to the needs of the labor market in times of the pandemic.

The weights for the dimensions and indicators used in our model are selected by the following multidimensional poverty normative weights (see Decancq and Lugo 2013). Each dimension is given an equal weight (1/6), and within a dimension, indicators are given equal weights. In Table 1, we also report weights for each dimension and indicator.

Regression Analysis

Following Alkire et al. (2015), we estimate a regression model to explain multidimensional deprivation from labor market outcomes by individual and regional factors, as well as occupation types. The regression model enables us to identify partial effects of the identified covariates on the constructed deprivation measure. A binary deprivation score is considered as an outcome variable for each individual. The probability that the individual i identified as multidimensionally deprived, conditional on the information set embedded in the variable vector X_i, is represented as

$$\mathrm{Prob}\left(X_i\right) = G\left(X_i\beta\right) \tag{1}$$

where the function $G(.)$ is the probability distribution. In case $G(.)$ is a normal probability distribution function, we estimate a probit model.[5]

Our primary interest is to evaluate marginal effects for covariates. For a continuous covariate, the marginal effect is defined as

[5] Alternatively, $G(.)$ can be a logistic function, in which case we estimate a logit model. We also estimate the logit model, and the results are qualitatively very similar to those of the probit model (available upon request).

$$\frac{\partial \text{Prob}(X)}{\partial x_j} = \beta_j(X\beta) \tag{2}$$

evaluated at the mean values of variables in vector X. For a discrete x_j, the partial effect is the difference in probabilities evaluated at the adjacent values of x_j.

We also estimate models by pooling observations from 2018 and 2020 together and running interactions with a binary variable on a gender type. In the first model, we interact gender with the year dummy to assess the change in the gender-gap in labor market deprivations during the pandemic. In the second case, we interact gender, marital status and the year, to capture the change in gender gap for married women. The two specifications are estimated with and without control of occupations, to capture the compositional effect of occupations on the change in gender gap.

Data

We use the Armenian Labor Force Survey (LFS) data from 2018 and 2020. We drop from the data individuals who did not search for a job at the moment of an interview and also are unlikely to rejoin the Armenian labor force later. That is, we aim to consider individuals in the sample not in a job search as potential job seekers, who are likely to join the Armenian labor market at a later stage. For this purpose, we drop individuals aged 63 (retirement age) or older, who are not in a job search and are considered as (i) too old, (ii) do not want to work or (iii) have some other reason not to work. Also, we drop individuals who are not in a job search because of emigration intentions. Initially, we observe 1376 and 1825 respondents from the years 2018 and 2020. After dropping such cases, we obtain 1,232 and 1,714 observations for the corresponding years. In the 2020 data, there are 888 respondents (51.81 percent) who separated from a job in 2019. The corresponding number of respondents in 2018 is 595 (48.30 percent). In Table 2 we report summary statistics for variables converted to deprivation measures. We report summary statistics for job-separated individuals in the year of an interview in Appendix B (Table 9).

Education level and vocational education/training are the measurements for which deprivation rates are quite high. Respectively, contributions to the deprivation measure (adjusted headcount ratio) of these dimensions are expected to be high. In 2020, the proportion of job-separated respondents with lower than secondary education is 62.5 percent, while the corresponding proportion in 2018 is 61.6 percent. The difference, however, is not significant at any conventional level. Regarding the vocational education/ training, the positive difference in deprivation is 2.2 percentage points, and the difference is significant at the one-percent level. In 2020, deprivation from occupation match is lower by 3.5 percentage points (with 10-percent significance), suggesting that in times of the pandemic job-separated individuals are considered to be deprived from an occupation less than in 2018. Qualitatively similar results are obtained for samples of individuals who separated from a job in the current year.

We observe high deprivation from demand factors for separating from a job. The first two indicators (*staff reduction/dissolution of the organization/lack of client/*

Table 2 Summary statistics of deprivation measures from 2018 and 2020 dataset

Variables (deprivation measures)	2018			2020			Non-deprived	Dep-rived
	N	Mean	Std. dev.	*N*	Mean	Std. dev.		
Education level	1232	0.616	0.487	1714	0.625	0.484	0	1
Vocational education / training	1232	0.945	0.228	1714	0.967	0.179	0	1
Occupation match	1232	0.550	0.498	1714	0.515	0.500	0	1
Demand factors (reasons) for separating from a job								
Staff reduction / dissolution of the organization / lack of client/ customer / temporary lay-off	1232	0.184	0.388	1714	0.260	0.439	0	1
End of a temporary / seasonal / one-time job	1232	0.529	0.499	1714	0.533	0.499	0	1
Low wages	1232	0.031	0.173	1714	0.023	0.149	0	1
Indicator	1232	0.744	0.436	1714	0.816	0.387	0	1
Supply factors (reasons) for separating from job								
Illness/disability/care of a sick family member	1232	0.041	0.199	1714	0.072	0.258	0	1
Household chores/family circumstances	1232	0.002	0.049	1714	0.009	0.096	0	1
Indicator	1,232	0.044	0.205	1,714	0.081	0.273	0	1
Demand factors for not looking for a job								
Waiting for the work/work season to resume	605	0.291	0.455	1084	0.440	0.497	0	1
Considered too young/too old to find a job	605	0.012	0.107	1084	0.003	0.053	0	1
Lack of jobs in the area	605	0.119	0.324	1084	0.179	0.384	0	1
Indicator	605	0.421	0.494	1084	0.622	0.485	0	1
Supply factors for not looking for a job								
Household chores/family circumstances	605	0.064	0.246	1084	0.020	0.141	0	1
Illness/injury/incident	605	0.104	0.306	1084	0.077	0.266	0	1
Child-care	605	0.188	0.391	1084	0.137	0.344	0	1
Indicator	605	0.253	0.435	1084	0.158	0.365	0	1

Table 2 (continued)

Variables (deprivation measures)	2018			2020			Non-deprived	Dep-rived
	N	Mean	Std. dev.	*N*	Mean	Std. dev.		
Demand factors for not finding a job								
Lack/absence of workplaces corresponding to an occupation/qualification	627	0.094	0.292	630	0.098	0.298	0	1
Low wage/income	627	0.026	0.158	630	0.013	0.112	0	1
Lack of knowledge in languages/IT (computer, internet, etc.)	627	0.003	0.056	630	0.003	0.056	0	1
Lack of job-search competencies	627	0.006	0.08	630	0.013	0.112	0	1
Indicator	627	0.129	0.336	630	0.127	0.333	0	1
Supply factors for not finding a job								
Lack/absence of workplaces	627	0.659	0.475	630	0.695	0.461	0	1
Low wage/income	627	0.107	0.309	630	0.067	0.25	0	1
Low wage/income	627	0.027	0.163	630	0.021	0.142	0	1
Considered too young/too old	627	0.002	0.04	630	0.002	0.04	0	1
Inclination for discrimination (disability/religion/appearance/family status)	627	0.003	0.056	630	0.000	0.000	0	1
Indicator	627	0.797	0.402	630	0.784	0.412	0	1

customer/temporary lay-off and *end of a temporary/seasonal/one-time job*) are key to capture the role of labor conditions on separating from a job. Substantial differences are also observed among supply factors of job separation with higher values in 2020, indicating that changes in labor market outcomes from the job-separation perspective cannot be merely explained by demand factors.

Regarding the measurements behind the dimension of not looking for a job, demand factors dominate. High values and positive differences in 2020 are observed for the measurements *waiting for the work/work season to resume* and *lack of jobs in the area.* Measurements of supply factors, on the other hand, reveal higher deprivation in 2018, suggesting that while *household chores*, *illness* or *child-care* are not reasons for searching for a job, they are among the reasons behind job separation. In times of the pandemic, family members who separated from a job seem to be eager to compromise unpaid household work for a job.

Interestingly, we do not find considerable differences in measurements in 2018 and 2020 within demand and supply factors for not finding a job. Formal two-sample proportion tests do not reject equality for these indicators, as well as for most of the measurements constituting indicators. This observation suggests that identified demand and supply factors for not finding a job alone cannot explain deterioration of labor market opportunities during the first year of the COVID-19.

Multidimensional Deprivation Analysis

Estimates of Multidimensional Deprivation

Table 3 shows the estimates of multidimensional deprivation including the headcount ratio (H), the average intensity of deprivations (A) and the adjusted headcount ratio (M0), calculated from 2018 and 2020 datasets. We estimate multidimensional deprivation measurements for cut-off values 0.1–0.9. For values above 0.6, H and $M0$ are zero. With the increase in the poverty cut-off value (k), the proportion of population defined as deprived (H) decreases, as fewer individuals are deprived in

Table 3 Multidimensional deprivation indexes

k	*H* (proportion of deprived)			*A* (average intensity of deprivation)			*M0* (adjusted headcount ratio)		
	2018	2020	Diff.	2018	2020	Diff.	2018	2020	Diff.
0.1	0.986	0.992	0.006***	0.491	0.498	0.007	0.484	0.494	0.010*
0.2	0.965	0.970	0.005	0.498	0.506	0.008	0.481	0.491	0.010
0.3	0.858	0.893	0.035***	0.529	0.528	− 0.001	0.454	0.471	0.017***
0.4	0.679	0.714	0.034***	0.580	0.577	− 0.004	0.394	0.411	0.017***
0.5	0.612	0.658	0.046***	0.598	0.590	− 0.008	0.366	0.388	0.022***
0.6	0.308	0.319	0.010***	0.667	0.667	0.000	0.206	0.212	0.007***
0.7	0	0	0				0	0	0

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

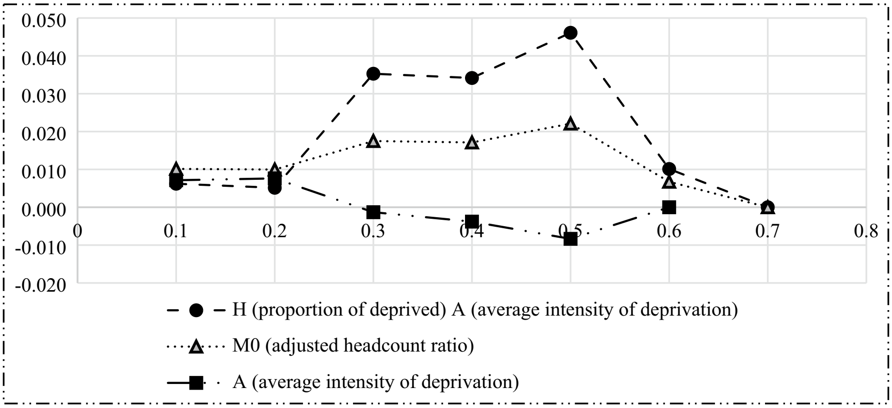

Fig. 2 Differences in multidimensional deprivation measurements between 2020 and 2018

more indicators. On the other hand, the average intensity of deprivation increases because the remaining deprived individuals are deprived in more indicators. The adjusted headcount ratio also decreases in k, as the adjustment is on the basis of per capita which includes both deprived and non-deprived individuals.

In Table 3, the third column for each index is the difference between 2020 and 2018 measures, calculated for each cut-off. For a given cut-off, the proportion of deprived (H) and adjusted headcount ratio (M0) are higher in 2020. That is, on average, *individuals representing (job-separated) labor force in the country, were more exposed to multidimensional deprivation from labor market outcomes in 2020, compared to 2018.* In both years, the proportion of deprived drastically decays at $k = 0.6$ and converges to zero at $k = 0.7$. The dramatic decay is reflected both in H and M0 indexes.

In Fig. 2 we plot the differences in deprivation measurements from 2020 and 2018 against cut-off values. For both headcount- and adjusted headcount ratios, the difference is the largest at $k = 0.5$ and it decays afterwards. The second highest picks are observed at $k = 0.2$. The difference in the average intensity of deprivation is the largest at $k = 0.2$. Also, the figure indicates that when differences in H and M0 get closer, the difference in deprivation intensity among deprived (A) increases. For job-separated individuals who are particularly vulnerable to labor market outcomes (smaller cut-offs), the average intensity of deprivation is higher in 2020. This implies that deprived individuals, initially vulnerable to labor market conditions, have suffered more in times of the pandemic. The pattern is reversed for the cut-off in the range (0.3–0.5) and the difference collapses to zero at $k = 0.6$.

Overall, we conclude that multidimensional deprivation from labor market outcomes is systematically larger in 2020. The two measurements, H and M0, suggest that labor market conditions deteriorated in 2020, making job-separated residents in Armenia more exposed to deprivation from labor market outcomes in times of the pandemic. *Average intensity of deprivation did not change significantly, indicating that the deprivation intensity "rule" remained invariant. While there is a lot* *of action occurring at the extensive margin (captured by headcount- and adjusted headcount ratios), we do not observe substantial shifts at the intensive margin (captured by the average intensity of deprivation) in 2020, compared to 2018.*

Contributions Analysis

We report contributions of dimensions and indicators to the adjusted headcount ratio M0 in Table 4, for the cut-off value 0.3. Equation (9) in Appendix A implies that if the contribution is larger than the weight in one dimension (indicator), individuals with a deprivation status are deprived more in that dimension (indicator). Dimensions on education categories contribute to multidimensional deprivation from labor market outcomes most. Vocational education/training contributes to the deprivation index the highest in both years. Our finding is supported by earlier studies showing that people without professional qualifications are much more vulnerable to losing a job (Körner et al. 2012; Sehnbruch et al. 2015). The second highest contributor is the education level. This is in line with the emerging literature arguing that negative labor market outcomes are more prevalent among less educated workers (Adams-Prassl et al. 2020; Aum et al., 2020; Cowan 2020; Montenovo et al. 2020). The third highest contributor in both years is the occupation match. In 2018, occupation match contributed to the adjusted headcount ratio by 20.1 percent (the corresponding value for 2020 is 18.2 percent). As Dasgupta and Murali (2020) claim, the COVID-19 unequal impact on the labor market is due to the workers' differentiated skills.

Contributions of dimensions 1-3 fall below their weights, suggesting that high deprivation observed in both regular and crisis times cannot be merely explained by the reasons of job separation, no job-search and/or failure to find a job. However, their variation form regular to the crisis periods can lead to significant changes in deprivation measures as we observe from the previous sub-section. For dimensions 1-2 (reasons for job separation and not looking for a job), we observe higher contributions in 2020, mostly stemming from demand factors. That is, *excessive deprivation from these dimensions in times of the pandemic is largely attributed to demand factors.* The argument is confirmed by large differences in headcount and adjusted-headcount ratios between 2020 and 2018, when the measurements utilize only the dimensions that are more sensitive to unexpected macroeconomic events in the labor market (dimensions 1-3). We report the multidimensional deprivation measurements with these dimensions in Table 10, Appendix B. Indeed, large differences in headcount and adjusted-headcount ratios between 2020 and 2018 confirm the relevance of these indicators (and most of dimensions 1 and 2) when comparing to the differences with the full set of dimensions (Table 3). We also report contributions (Table 11) to underline the crucial role of these dimensions and indicators in explaining deprivation changes in 2020. The dominance of demand factors in dimensions 1 and 2 corroborates our observations from data inspection that *deprivation from labor market opportunities in times of the pandemic are mostly driven by industry needs rather than explained by individual capabilities failing to meet labor market conditions.* These results support the literature on the push factors for job-separation and job-search behavior (Semmer et al. 2014; Lee and Mitchell

Table 4 Contributions analysis for $k = 3$

Dimension	Weight	Contribution		Indicator	Weight	Contribution	
		2018	2020			2018	2020
1. Reasons for separating from a job	0.167	0.136	0.15	Demand factors	0.083	0.128	0.136
				Supply factors	0.083	0.008	0.014
2. Reasons not looking for a job	0.167	0.055	0.085	Demand factors	0.083	0.037	0.069
				Supply factors	0.083	0.017	0.016
3. Main obstacle in finding a job/launching your own business?	0.167	0.079	0.053	Demand factors	0.083	0.069	0.047
				Supply factors	0.083	0.01	0.006
4. Education	0.167	0.226	0.221	Education	0.167	0.226	0.221
5. Vocational education/training	0.167	0.302	0.309	Did you take any course, practice, private courses, vocational / training, regular or occasional lasting even a few hours or days during the month (including the surveyed week)?	0.167	0.302	0.309
6. Occupation match	0.167	0.201	0.182	Do you think your occupation (both formal and informal) is useful in your job/ in finding a job?	0.167	0.201	0.182

1994; Maertz and Campion 2004). The literature suggests that employment type, such as non-standard, seasonal, (Lee et al. 1999; Augner 2015) and organizational factors, such as becoming more technology savvy, downsizing, management issues (Zavodny 2003; Grimshaw et al. 2001; Mourdoukoutas 1988) are the driving factors for job separation and further not looking for a job.

Analysis for Individuals Separated from a Job in the Current Year

Next, we estimate the multidimensional deprivation measures and conduct contribution analysis for individuals separated from a job in the current year of an interview. That is, we compare the measures for respondents who separated from a job in 2020 with the corresponding measures for respondents with the same status in 2018. In the two surveys, respondents answer the question "How long have you been out of work?". Possible answers are "up to 3 months", "3–6 months", "6–9" months, "9–12 months", "1–2 years", "2–3 years" and "more than 3 years". In the baseline analysis, we selected individuals who have been out from the job market for the period up to 1 year. The first lockdown in Armenia took place in March 2020, but the awareness of COVID-19 in the country and the world, as well as pandemic-related global developments could potentially have resulted in labor market adjustments earlier than March. The limitation of this analysis is the reduced sample size. From Table 9, Appendix B, we learn that there are 579 and 697 such respondents in 2018 and 2020, respectively.

In Table 5, we report the three multidimensional deprivation indexes. Overall, we observe a pattern similar to the one identified from full samples. Deprivation from labor market outcomes in times of COVID-19 is higher than that in 2018 for individuals who have been separated from a job in the current year. Qualitatively similar results are also obtained for the average intensity of deprivation.

We report contributions for limited samples in Table 6. Similar to the baseline model, vocational education/training is the major contributor to the adjusted-headcount ratio in both years. Education level and occupation match are the second and third contributing factors, respectively. The dimension *reasons for separating from a*

Table 5 Multidimensional deprivation indexes for individuals separated from a job in the current year

k	*H* (proportion of deprived)			*A* (average intensity of deprivation)			*M0* (adjusted headcount ratio)		
	2018	2020	Diff.	2018	2020	Diff.	2018	2020	Diff.
0.1	0.984	0.993	0.008***	0.495	0.499	0.003	0.488	0.495	0.008***
0.2	0.965	0.966	0.000	0.502	0.508	0.006	0.484	0.491	0.006
0.3	0.869	0.894	0.025***	0.530	0.529	− 0.001	0.460	0.473	0.012***
0.4	0.696	0.706	0.010	0.579	0.581	0.002	0.403	0.410	0.007
0.5	0.627	0.657	0.030*	0.596	0.593	− 0.003	0.374	0.390	0.016**
0.6	0.306	0.340	0.034***	0.667	0.667	0.000	0.204	0.227	0.023***
0.7	0	0	0				0	0	0

***p<0.01, **p<0.05, *p<0.1

Table 6 Contribution analysis ($k = 3$) for individuals separated from a job in the current year

Dimension	Weight	Contribution		Indicator	Weight	Contribution	
		2018	2020			2018	2020
1. Reasons for separating from a job	0.167	0.138	0.152	Demand factors	0.083	0.132	0.142
				Supply factors	0.083	0.006	0.01
2. Reasons not looking for a job	0.167	0.058	0.096	Demand factors	0.083	0.044	0.084
				Supply factors	0.083	0.013	0.011
3. Main obstacle in finding a job/launching your own business?	0.167	0.074	0.043	Demand factors	0.083	0.063	0.037
				Supply factors	0.083	0.011	0.006
4. Education	0.167	0.23	0.223	Education	0.167	0.23	0.223
5. Vocational education/training	0.167	0.301	0.307	Did you take any course, practice, private courses, vocational / training, regular or occasional lasting even a few hours or days during the month (including the surveyed week)?	0.167	0.301	0.307
6. Occupation match	0.167	0.198	0.18	Do you think your occupation (both formal and informal) is useful in your job/ in finding a job?	0.167	0.198	0.18

Table 7 Regression results

	Model 1. Job separation within a year		Model 2. Job separation within a current year	
	(1)	(2)	(3)	(4)
Variables	2018	2020	2018	2020
Age	− 0.0008	− 0.0015***	− 0.0006	− 0.0019***
	(0.0006)	(0.0004)	(0.0009)	(0.0007)
Female	− 0.0091	0.0205	0.0064	0.0439**
	(0.0196)	(0.0138)	(0.0299)	(0.0200)
Married	0.0289	0.0524***	0.0365	0.0798***
	(0.0192)	(0.0130)	(0.0273)	(0.0204)
Rural	0.0734***	0.0645***	0.0258	0.0583**
	(0.0257)	(0.0190)	(0.0394)	(0.0265)
Non-capital urban	0.0302	0.0376**	− 0.0074	0.0428*
	(0.0227)	(0.0165)	(0.0329)	(0.0246)
Legislators, senior officials, managers	− 0.4044***	− 0.1846***	− 0.4005***	− 0.1748***
	(0.0730)	(0.0446)	(0.1131)	(0.0667)
Professionals	− 0.3222***	− 0.2141***	− 0.3183***	− 0.2469***
	(0.0354)	(0.0228)	(0.0514)	(0.0382)
Technicians, professionals	− 0.2355***	− 0.2112***	− 0.2495***	− 0.2124***
	(0.0328)	(0.0229)	(0.0486)	(0.0343)
Clerks	− 0.1976***	− 0.1743***	− 0.2406***	− 0.2280***
	(0.0458)	(0.0343)	(0.0615)	(0.0477)
Service and sales workers	− 0.1648***	− 0.1267***	− 0.1553***	− 0.1208***
	(0.0273)	(0.0185)	(0.0371)	(0.0259)
Craft workers	− 0.0312	− 0.0515***	− 0.0331	− 0.0817***
	(0.0277)	(0.0181)	(0.0399)	(0.0251)
Operators and assemblers	− 0.0419	− 0.0354	− 0.1047**	− 0.0546
	(0.0400)	(0.0284)	(0.0486)	(0.0360)
Pseudo *R*-square	0.2435	0.2220	0.2426	0.2571
Observations	1,232	1,713	579	697

Standard errors in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Reference category is "Agricultural workers and elementary occupations". Marginal effects are reported

job has a higher contribution stemming from demand factors for 2020, compared to that in the baseline model. Contribution from dimension 2 (reasons for not looking for a job) is also larger for the limited sample and with a higher value for 2020. As in the case of dimension 2, the contribution largely stems from demand factors. These observations suggest that the adverse effects from the industry side are even stronger for individuals who separated from a job in the year of the pandemic.

We also report deprivation measurements based on dimensions 1–3 (Table 11, Appendix B), as we did for the baseline case (Table 10, Appendix B). When comparing headcount ratios, we observe that the difference is smaller in the limited sample for the cut-off 0.1. This suggests that individuals particularly vulnerable to deprivation from labor market outcomes did not bear extra pain if they were separated from a job in times of the pandemic.

Regression Model

Overall, the emerging literature demonstrates that globally, negative labor market outcomes are more prevalent among younger, less educated, lower-waged, and non-standard workers (Aum et al. 2021; Cowan 2020; Montenovo, et al. 2020). This motivates us to consider individual factors in our regression model.

In Table 7, we report probit regression results for 2018 and 2020 datasets. In Model 1 (columns 1–2) we include individuals who separated from a job within the year prior to an interview. In Model 2 (columns 3–4) we include individuals separated from a job within the current year. In Appendix B (Table 12), we also report regression results with the dependent variable constructed from dimensions 1–3. The covariates are age, female, rural and non-capital urban dummies, as well as ISCO occupation types. We bring together agricultural workers (6) and elementary occupations (9) categories and treat as a reference category.

Age enters with a negative coefficient in all models, but significant only for 2020.[6] A ten-year older individual observed in 2020 and separated from a job within the last year (column 2, Model 1) is less likely to be deprived from labor market outcomes by 1.5 percentage points. The corresponding magnitude for an individual separated from a job in 2020 (column 4, Model 2) is 1.9 percentage points. When restricting the dimensions included in the dependent variable, age is significant only in the 2018 model (column 1 in Table 12, Appendix B) with a positive sign. Overall, these results suggest that higher-age (job-separated) individuals are less likely to be deprived from labor market outcomes in times of the pandemic.

Probability of being deprived from labor market outcomes is higher for female respondents in 2020. Significance is, however, obtained only in Model 2. Deprivation gap between women and men amounts to 4.39 percentage points, significant at the five-percent level. In models with narrowed dimensions, deprivation gaps between women and men are even larger, 6.39 and 9.01 percentage points for all individuals and individuals separated from a job in a current year, respectively, both significant at the five-percent level (Table 12). Our finding is in line with existing evidence showing that during the pandemic women have experienced more difficulties (such as unemployment) in labor markets than men (Alon et al. 2020a; Reichelt et al. 2020; Ham 2021; Tverdostup 2022). To certain extent this might be explained by the gender composition of different sectors of the economy. Also, the concerned workforce might face employment challenges due to the shutdown of child-care,

[6] We do not observe a non-linear effect of age in either of our specifications.

schooling, home and family health care services (Dingel and Neiman 2020). Caregiver roles are mostly assumed by women (Signorelli et al. 2012; Schoonbroodt 2018; Tverdostup 2022), the burden being more ponderous for married women. We explore these potential channels in our interaction analysis section. Also, women's jobs tend to be given a lower priority in many countries since they are more likely to have part-time, lower-income, and less secure jobs (Kim 2000; Boniol et al. 2019; Johnson and Williams 2020).

Married individuals are systematically more deprived in labor markets in the year of the pandemic. This result does not corroborate similar findings in the literature which suggest that married workers have a lower chance of losing their jobs (Balde et al. 2020; Guven et al. 2020). In our study we observe that, in 2020, deprivation gap between married and non-married individuals is 5.24 percentage points (column 2, Model 1). The gap is even larger in Model 2, 7.98 percentage points. Interestingly, the gap is observed in both 2018 and 2020 with higher magnitudes in models with the dependent variable constructed from the three dimensions (Table 12). We conclude that deprivation gap between married and non-married individuals observed in 2020 largely owes to dimensions among education, vocation education/training and occupation match.

In 2018, the likelihood of deprivation in rural areas, as compared with the capital city, is higher by 7.34 percentage points (column 1, Model 1). The corresponding difference in 2020 is 6.45 (column 2). Interestingly, when narrowing the pool of individuals, deprivation gap is observed only in 2020, with the magnitude of 5.83 percentage points and five-percent significance (column 4). That is, in 2020 the type of settlement still matters in labor market deprivation for individuals, who have been separated from a job in the current year. When restricting the number of dimensions, the deprivation gap is not significant anymore (Table 12). Regarding the residents in non-capital urban areas, excessive (10-percent significant) deprivation compared to residents in the capital city is observed in 2020, with the magnitude of 4.28 percentage points (column 4, Table 7).

Finally, we study deprivation differences owing to occupation types. On one hand, respondents belonging to the reference category (agricultural workers and elementary occupations) reveal the highest deprivation compared to any other occupation type. On the other hand, most occupations suffered from the pandemic more, as the pandemic has hit individuals with diverse occupations even more severely than individuals working in agriculture and/or holding elementary occupations. Exceptions are craft workers and operators/assemblers. For example, in 2018 individuals previously working as service and sales workers are deprived by 16.48 percentage points less than individuals previously working as an agriculture worker or holding an elementary occupation (column 1, Model 1 in Table 7). In times of the pandemic, the difference decreased to 12.67 percent (column 2, Model 1). In Model 2 (Table 7), the magnitudes and the difference do not differ much, but they do in models with limited dimensions (Table 12, Appendix B). We observe that in 2018 service and sales workers are much less deprived (32.65 and 35.40 percentage points in Models B1 and B2, respectively), while the gap has dramatically decreased to 25.00 and 23.17 percentage points. Further, when taking the dimensions responsible for short-term variation of deprivation measurements into the binary deprivation score,

Table 8 Regression results with interacted variables

	Model 3. Interaction between gender and year		Model 4. Triple interaction: gender, marital status, and year	
Variables	(1)	(2)	(3)	(4)
Male × 2018	0.0111	0.0846***		
	(0.0156)	(0.0169)		
Male × 2020	0.0203	0.0950***		
	(0.0148)	(0.0160)		
Female × 2020	0.0444***	0.0450***		
	(0.0151)	(0.0173)		
Male × Not married × 2018			− 0.0221	0.0551**
			(0.0232)	(0.0266)
Female × Not married × 2018			− 0.0048	− 0.0043
			(0.0222)	(0.0258)
Male × Married × 2018			0.0283	0.0986***
			(0.0190)	(0.0208)
Male × Not married × 2020			− 0.0017	0.0861***
			(0.0220)	(0.0249)
Female × Not married × 2020			− 0.0034	− 0.0004
			(0.0202)	(0.0235)
Male × Married × 2020			0.0326*	0.1004***
			(0.0180)	(0.0197)
Female × Married × 2020			0.0770***	0.0747***
			(0.0200)	(0.0227)
Age	− 0.0012***	− 0.0000	− 0.0012***	0.0000
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Married	0.0436***	0.0348***		
	(0.0110)	(0.0127)		
Rural	0.0675***	0.1618***	0.0668***	0.1608***
	(0.0146)	(0.0162)	(0.0145)	(0.0162)
Non-capital urban	0.0358***	0.0836***	0.0363***	0.0837***
	(0.0131)	(0.0153)	(0.0130)	(0.0153)
Legislators, senior officials, managers	− 0.2697***		-0.2689***	
	(0.0386)		(0.0384)	
Professionals	− 0.2562***		− 0.2547***	
	(0.0196)		(0.0196)	
Technicians, professionals	− 0.2221***		− 0.2226***	
	(0.0186)		(0.0185)	
Clerks	− 0.1843***		− 0.1853***	
	(0.0269)		(0.0268)	
Service and sales workers	− 0.1423***		− 0.1440***	
	(0.0154)		(0.0154)	

Table 8 (continued)

Variables	Model 3. Interaction between gender and year (1)	(2)	Model 4. Triple interaction: gender, marital status, and year (3)	(4)
Craft workers	− 0.0433***		− 0.0442***	
	(0.0156)		(0.0156)	
Operators and assemblers	− 0.0382		− 0.0391*	
	(0.0233)		(0.0232)	
Pseudo R-square	0.2296	0.0814	0.2326	0.0838
Observations	2945	2946	2945	2946

Standard errors in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Reference category is "Agricultural workers and elementary occupations". Marginal effects are reported. In Models (1) and (2), the base category for interacted variables *gender* and *year* is Female × 2018. In Models (3) and (4), the base category for the interacted variables *gender*, *marital status*, and *year* is Female × Married × 2018

operators and assemblers suffer more in times of the pandemic comparted to individuals in the reference category. Overall, we conclude that deprivation from labor market outcomes has deepened during the COVID-19 for most of the occupations.

Interaction Analysis

In this section, we further explore women's deprivation from labor market outcomes in the multivariate regression framework. We address the question whether women in the year of pandemic were more exposed to deprivation by pulling observations from 2018 and 2020 in one model. To estimate the deprivation change, we interact gender and year dummies, taking the base category as *female × 2018*. Also, we estimate the model with and without occupation types, to assess the responsiveness of gender-gap change to the composition of occupation types. Findings from earlier studies on the COVID-19 show that the impact and magnitude of the crisis vary with different dimensions, including the industry/occupation (Ham et al. 2021; Alon et al. 2020; Tverdostup 2022). We report regression results from these specifications in columns (1–2), Table 8.[7] From the table, we observe that women in 2020 are more likely to be deprived from labor market outcomes by 4.44 percentage points, compared to 2018. When controlling for occupation types, the corresponding deprivation increases by 4.5 percentage points. A rather tiny difference in the two coefficients suggests that the increased deprivation is not contingent on occupation types. It is documented that education and health care are much less affected in typical recessions as compared to manufacturing and residential construction sectors in

[7] Regression results from these specifications for respondents separated from a job in the current year is reported in Table 13, Appendix.

which males' employment is more concentrated (Alon et al. 2020). Thus, women are highly represented in sectors with relatively stable employment over the cycle. Our results suggest that gender gap in labor market deprivation do not differ within occupation and across occupations.

Next, we interact gender, marital status, and year categories to identify the change in deprivation among married women in the year of pandemic. Evidence shows that family-related elements, namely, marital status and the presence of children in the household, can condition the job separation probability (Frederiksen 2008). Married women are vulnerable towards deprivation from labor market outcomes due to housework and child-care (Blundell and MaCurdy 1999). Our regression specification allows us to assess the change (if any) in the gender gap in the year of pandemic. As in the previous case, we estimate the model with and without occupation types to account for potential occupation-composition effects. In this case, the base category is married female observed in 2018. We report the estimates of the specifications in the last two columns of Table 8. In the year of pandemic, married women are more likely to be deprived from labor market outcomes by 7.7 percentage points, compared to 2018. The deprivation increase across occupations is less, 7.47 percentage points, but the difference is not significant.

We report estimation results from Models 3 and 4 for respondents separated from a job in the current year in Table 12, Appendix. Interestingly, an upward change in gender gap for Model 3 is not significant. This suggests that women separated from a job in the year of pandemic are not necessarily deprived more than women separated from a job in 2018. However, when comparing deprivation for married women, excessive deprivation is 5-percent significant (7.79 and 8.92 percentage points within occupation and across occupations, respectively). The difference between the two coefficients is not significant, confirming the previous result that deprivation changes are not conditioned by the composition of occupation types.

Conclusion

Long-term unemployment increases the risk of exposure to poverty and social exclusion (Hagenaars et al. 1994; Atkinson 1998). On the top of economic deprivation, unemployment can result in social deprivation that leads to a decline in self-respect and an increase in social isolation. In this light, we aim to explore labor market related deprivation factors for job-separated individuals in times of the COVID-19. Our study contributes to the discourse of the Quality of Employment (Gonzalez et al. 2021; Sehnbruch et al. 2020), whereby we retain the key exploration aspects, such as motivation for job separation, job-search behavior, obstacles in finding a job, education forms and occupation match.

Using Armenian Labor Force Survey 2018 and 2020 datasets, we select individuals who have been separated from a job during the year prior to an interview. We also conduct the study for individuals who separated from a job in the current year, which enables to identify individuals who separated from their jobs in the early phase of the pandemic. Large deprivation differences in 2018 and 2020 are mostly driven by demand factors, stemming from the dimensions related to *reasons for separating from a job* and *reasons for not searching for a job*.

Education related dimensions contribute to multidimensional deprivation from labor market outcomes the most. Education with the threshold of secondary level is a contributor to the adjusted headcount ratio both in 2018 and 2020. Despite its poor/inadequate post-Soviet quality, education still plays a non negligible role in shaping an individual's status in the labor market. Investing in education is critical to increase resilience of social wellbeing towards adverse shocks both at global and local levels.

Similar to existing studies, we observe a systematic gender gap in deprivation from labor market outcomes. Our findings indicate that women are sensitive to changes in labor market conditions in crisis times. The gender gap is further amplified for married women. This finding suggests that policies aimed at decreasing gender gaps in labor market outcomes should focus on creating protection mechanisms, such as raising barriers for firing women, incentivizing employers to provide women more flexible working conditions and hours (for instance, remote work and flexible working time schedule), and providing more attractive employment packages covering insurance, child-care and maternity leave.

We also study deprivation differences driven by occupation types. Respondents with a low skillset reveal the highest deprivation compared to any other occupation type. We find that most occupations suffered more in times of the pandemic. Interestingly, gender gap in deprivation is not contingent on the composition of occupations, suggesting that gender gap is rather uniform across and within industries.

While our study does not shed light on habit and social-psychological characteristics, it provides several important insights for understanding the specifics of socio-economic developments through the lenses of labor market outcomes. Rural-urban differences suggest that the Government strategies and derived policies need to be settlement-type specific, with a strong focus on highlighted dimensions from the labor market perspectives, which are education, unemployment and occupation match.

By unfolding the deprivation determinants, we provide insights for public and private stakeholders in developing opportunities for accessible employment, skills enhancement and minimizing the mismatch between the outputs of educational systems and the labor market needs. Designing policies that are targeted at the most vulnerable subgroups will contribute to soften devastating and long-term consequences led by deprivations from labor market opportunities. This discourse is important provided that unemployment breeds unemployment and has long-lasting negative effects on income and subsequent employment chances, in particular, for new entrants in the job market (Schmillen and Umkehrer 2013; Moller and Umkehrer 2015). While our data enables us to focus on the changes in labor market conditions in times of the pandemic, there is uncertainty about whether observed deprivation forms will be long-lived. From this perspective, our study opens an avenue for further research which shall incorporate a longer period of time enabling to assess long-term deprivation effects.

Appendix A: Dual Cut-off Framework

The unit of our analysis is individuals in Armenia. Our outcome variable is based on the deprivation (from labor market outcomes) score, and the methodology for constructing the score is described below. Let $X_{i,j}$ denote the achievement of individual i in dimension j for all $i = 1, 2, \ldots, n$, and $j = 1, 2, \ldots, d$. We use a dual cut-off framework by Alkire and Foster (2011), which identifies multidimensional poor households. In our case, we identify individuals deprived from labor market outcomes multidimensionally. The *deprivation cut-off* (denoted as $Z_j > 0$) is the deprivation line in dimension or indicator j. If the achievement of individual i is higher than the cut-off, $X_{i,j} \geq Z_j$, individual i is not deprived in dimension/indicator j. Otherwise, the individual i is deprived in this dimension/indicator. If individual i is deprived in dimension j, then we denote that the deprivation status value is $g_{ij} = 1$, otherwise, $g_{ij} = 0$. The second cut-off is the overall *deprivation cut-off* k $(0 \leq k \leq 1)$, which is a pre-determined fraction of the total number of dimensions or indicators. That is, if we define deprivation measure as the individual being poor when it is deprived in 40 percent of total number of indicators then we assign a value $k = 0.4$. In this process, there are two steps to identify a deprived individual. First, by giving weight w_j to each dimension or indicator j such that $\sum_{j=1}^{d} w_j = 1$, we obtain the weighted deprivation status value $w_j g_{ij}$ and the deprivation score,

$$c_i = \sum_{j=1}^{d} w_j g_{ij}. \tag{3}$$

Second, we compare the deprivation score with deprivation cut-off for individual i and identify the (multidimensional) deprivation status. If $c_i \geq k$, individual i is considered to be deprived (and we will denote $c_i \text{as} c_i(k)$), otherwise $(\text{that is, if} c_i < k)$ non-deprived (in this case $c_i = 0$). The censored deprivation score $(c_i(k))$ captures the share of possible deprivations experienced by poor household i.

Three indicators are used to measure multidimensional deprivation: the headcount ratio (H), the average deprivation gap (A) and the adjusted headcount ratio (M_0). Dividing the number of the deprived individuals by the total number of the households, we can obtain the headcount ratio:

$$H = \frac{q}{n}, \tag{4}$$

where q is the number of deprived individuals for whom $c_i \geq k$. Average deprivation score *across the deprived* is represented by average deprivation gap,

$$A = \frac{\sum_{i=1}^{n} c_i(k)}{q}. \tag{5}$$

This gap index, also called intensity of deprivation, provides relevant information about multidimensional deprivation. Individuals experiencing simultaneous deprivations in a higher fraction of dimensions have a higher intensity score and are more deprived than others with a lower intensity. Based on these two measurements, the adjusted headcount ratio (M_0) can be obtained as:

$$M_0 = H \times A = \frac{q}{n} . \frac{\sum_{i=1}^{n} c_i(k)}{q} = \frac{\sum_{i=1}^{n} c_i(k)}{n} = \frac{\sum_{i=1}^{n} \sum_{j}^{d} g_{ij}(k)}{n}. \tag{6}$$

Here, $g_{ij}(k)$ is the weighed deprivation status specific to dimension j. The adjusted headcount ratio is the share of weighted deprivations experienced by deprived individuals divided by the number of individuals. If deprived individuals are deprived in all dimensions simultaneously, that is, intensity of poverty (A) is the highest, M_0 approaches H.

The raw headcount ratio of a particular indicator/dimension is calculated as a per cent of deprived individuals to total number of individuals. This concept is similar to that in use in unidimensional poverty measures. While the censored headcount ratio of dimension/indicator j, H_j^c is defined as the percentage of poor individuals who are deprived in j after the introduction of the dual cut-off:

$$H_j^c = \frac{\sum_{i=1}^{n} g_{ij}(k)}{w_j n} \tag{7}$$

The adjusted headcount ratio M_0 satisfies the additive decomposability principle (see Alkire and Foster 2011), so it can be decomposed by dimensions and subgroups. Using equations (4) with (5), M_0 can be written as the weighted sum of the censored headcount ratios:

$$M_0 = \sum_{j=1}^{d} w_j H_j^C. \tag{8}$$

The contribution of dimension j is

$$C_j = \frac{w_j H_j^C}{M_0} \tag{9}$$

Appendix B: See Tables 9, 10, 11, 12, 13 and figures

Table 9 Summary statistics of deprivation measures from 2018 and 2020 dataset for respondents separated from a job in the current year

Variables	2018 *N*	2018 Mean	2018 Std. dev.	2020 *N*	2020 Mean	2020 Std. dev.	Non-deprived	Dep-rived
Education level	579	0.637	0.481	697	0.631	0.483	0	1
Vocational education/training	579	0.943	0.232	697	0.961	0.193	0	1
Occupation match	579	0.547	0.498	697	0.512	0.500	0	1
Demand factors (reasons) for separating from job								
Staff reduction / dissolution of the organization / lack of client/ customer / temporary lay-off	579	0.174	0.380	697	0.337	0.473	0	1
End of a temporary / seasonal / one-time job	579	0.582	0.494	697	0.496	0.500	0	1
Low wages	579	0.017	0.130	697	0.027	0.163	0	1
Indicator	579	0.774	0.419	697	0.861	0.346	0	1
Supply factors (reasons) for separating from job								
Illness / disability / care of a sick family member	579	0.035	0.183	697	0.050	0.219	0	1
Household chores / family circumstances	579	0.000	0.000	697	0.007	0.084	0	1
Indicator	579	0.035	0.183	697	0.057	0.233	0	1
Demand factors for not looking for a job								
Waiting for the work / work season to resume	295	0.366	0.483	491	0.574	0.495	0	1
Considered too young / too old to find a job	295	0.007	0.082	491	0.004	0.064	0	1
Lack of jobs in the area	295	0.112	0.316	491	0.110	0.313	0	1
Indicator	295	0.485	0.501	491	0.688	0.464	0	1
Supply factors for not looking for a job								
Household chores / family circumstances	295	0.044	0.206	491	0.018	0.134	0	1
Illness / injury / incident	295	0.068	0.252	491	0.047	0.212	0	1
Child care	295	0.142	0.350	491	0.084	0.277	0	1
Indicator	295	0.186	0.390	491	0.102	0.303	0	1
Demand factors for not finding a job								
Lack/absence of workplaces corresponding to an occupation/qualification	284	0.099	0.299	206	0.126	0.333	0	1

Table 9 (continued)

Variables	2018			2020			Non-deprived	Dep-rived
	N	Mean	Std. dev.	*N*	Mean	Std. dev.		
Low wage/income	284	0.032	0.175	206	0.015	0.120	0	1
Lack of knowledge in languages/IT (computer, internet, etc.)	284	0.004	0.059	206	0.000	0.000	0	1
Lack of job-search competencies	284	0.014	0.118	206	0.005	0.070	0	1
Indicator	284	0.148	0.356	206	0.146	0.354	0	1
Supply factors for not finding a job								
Lack/absence of workplaces	284	0.623	0.485	206	0.699	0.460	0	1
Low wage/income	284	0.120	0.325	206	0.044	0.205	0	1
Low wage/income	284	0.032	0.175	206	0.010	0.098	0	1
Considered too young/too old	284	0.000	0.000	206	0.000	0.000	0	1
Inclination for discrimination (disability / religion / appearance / family status)	284	0.004	0.059	206	0.000	0.000	0	1
Indicator	284	0.778	0.416	206	0.752	0.433	0	1

Table 10 Multidimensional deprivation indexes with three dimensions

k	H (proportion of deprived)			A (average intensity of deprivation)			$M0$ (adjusted headcount ratio)		
	2018	2020	Diff.	2018	2020	Diff.	2018	2020	Diff.
0.1	0.942	0.970	0.028*	0.282	0.297	0.014	0.266	0.288	0.022*
0.2	0.654	0.756	0.101***	0.333	0.333	0.000	0.218	0.252	0.034***
0.3	0.654	0.756	0.101***	0.333	0.333	0.000	0.218	0.252	0.034***
0.4	0.000	0.000	0.000				0.000	0.000	0.000

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 11 Multidimensional deprivation indexes with three dimensions based on observations from the current year

k	*H (proportion of deprived)*			*A (average intensity of deprivation)*			*M0 (adjusted headcount ratio)*		
	2018	2020	Diff.	2018	2020	Diff.	2018	2020	Diff.
0.1	0.946	0.961	0.015*	0.283	0.302	0.019	0.267	0.290	0.023*
0.2	0.658	0.779	0.121***	0.333	0.333	0.000	0.219	0.260	0.040***
0.3	0.658	0.779	0.121***	0.333	0.333	0.000	0.219	0.260	0.040***
0.4	0.000	0.000	0.000				0.000	0.000	0.000

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 12 Regression results with the dependent based on three dimensions

	Model B1: Separated from a job within a last year		Model B2: Separated from a job within a current year	
	(1)	(2)	(3)	(4)
Variables	2018	2020	2018	2020
Age	0.0023**	− 0.0005	0.0023	− 0.0011
	(0.0011)	(0.0008)	(0.0016)	(0.0012)
Female	− 0.0427	0.0639**	− 0.0226	0.0901**
	(0.0336)	(0.0250)	(0.0514)	(0.0376)
Married	0.1452***	0.1094***	0.1431***	0.1686***
	(0.0326)	(0.0239)	(0.0482)	(0.0359)
Rural	0.1263***	0.1165***	0.0893	0.0470
	(0.0456)	(0.0350)	(0.0687)	(0.0530)
Non-capital urban	0.0297	0.0387	− 0.0519	0.0128
	(0.0428)	(0.0328)	(0.0631)	(0.0494)
Legislators, senior officials, managers	− 0.5589***	− 0.1262	− 0.3209	− 0.2595*
	(0.1473)	(0.1081)	(0.2376)	(0.1566)
Professionals	− 0.4033***	− 0.2078***	− 0.4050***	− 0.3678***
	(0.0628)	(0.0446)	(0.0950)	(0.0722)
Technicians professionals	− 0.2835***	− 0.2857***	− 0.2904***	− 0.2769***
	(0.0608)	(0.0442)	(0.0945)	(0.0638)
Clerks	− 0.2630***	− 0.2493***	− 0.3210**	− 0.3564***
	(0.0899)	(0.0715)	(0.1300)	(0.0963)
Service & sales workers	− 0.3265***	− 0.2500***	− 0.3540***	− 0.2317***
	(0.0463)	(0.0340)	(0.0678)	(0.0484)
Craft workers	− 0.1179***	− 0.0921***	− 0.1117**	− 0.1744***
	(0.0385)	(0.0285)	(0.0559)	(0.0441)
Operators and assemblers	− 0.2460***	− 0.0687	− 0.3406***	− 0.1845***
	(0.0551)	(0.0434)	(0.0823)	(0.0654)
Pseudo R-square	0.1289	0.0876	0.1424	0.1243
Observations	1,232	1,713	579	697

Standard errors in parentheses

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Reference category is "Agricultural workers and elementary occupations". Marginal effects are reported

Table 13 Regression results with interacted variables, based on observations from the current year

Variables	Model B3. Interaction between gender and year (1)	(2)	Model B4. Triple interaction: gender, marital status, and year (1)	(2)
Male × 2018	− 0.0133	0.0653***		
	(0.0234)	(0.0252)		
Male × 2020	− 0.0114	0.0642***		
	(0.0226)	(0.0246)		
Female × 2020	0.0297	0.0383		
	(0.0231)	(0.0268)		
Male × Not married × 2018			− 0.0533	0.0572
			(0.0333)	(0.0383)
Female × Not married × 2018			− 0.0038	0.0044
			(0.0325)	(0.0388)
Male × Married × 2018			0.0106	0.0741**
			(0.0280)	(0.0310)
Male × Not married × 2020			− 0.0521*	0.0444
			(0.0314)	(0.0358)
Female × Not married × 2020			− 0.0291	− 0.0189
			(0.0295)	(0.0349)
Male × Married × 2020			0.0131	0.0783***
			(0.0274)	(0.0303)
Female × Married × 2020			0.0779**	0.0892**
			(0.0317)	(0.0364)
Age	− 0.0012***	− 0.0000	− 0.0012***	0.0000
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Married	0.0616***	0.0402**		
	(0.0164)	(0.0192)		
Rural	− 0.0014**	0.0003	− 0.0014**	0.0005
	(0.0006)	(0.0006)	(0.0006)	(0.0007)
Non-capital urban	0.0457**	0.1492***	0.0475**	0.1493***
	(0.0224)	(0.0249)	(0.0220)	(0.0249)
Legislators, senior officials, managers	− 0.2733***		− 0.2656***	
	(0.0621)		(0.0616)	
Professionals	− 0.2807***		− 0.2776***	
	(0.0317)		(0.0316)	
Technicians, professionals	− 0.2329***		− 0.2314***	
	(0.0276)		(0.0274)	
Clerks	− 0.2357***		− 0.2368***	
	(0.0374)		(0.0371)	
Service and sales workers	− 0.1358***		-0.1381***	
	(0.0220)		(0.0218)	

Table 13 (continued)

Variables	Model B3. Interaction between gender and year (1)	(2)	Model B4. Triple interaction: gender, marital status, and year (1)	(2)
Craft workers	− 0.0585**		-0.0593***	
	(0.0227)		(0.0225)	
Operators and assemblers	− 0.0805***		-0.0809***	
	(0.0308)		(0.0304)	
Pseudo *R*-square	0.2385	0.0733	0.2442	0.0787
Observations	1276	1276	1276	1276

Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Reference category is "Agricultural workers and elementary occupations". Marginal effects are reported. In Models (1) and (2), the base category for interacted variables *gender* and *year* is Female × 2018. In Models (3) and (4), the base category for the interacted variables *gender*, *marital status*, and *year* is Female × Married × 2018

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References

Acemoglu, D., V. Chernozhukov, I. Werning, and M. D. Whinston (2020). A multi-risk SIR model with optimally targeted lockdown. NBER Working Paper No. 27102.

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh. 2020. Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics* 189: 104245.

Alaimo, L.S., A. Arcagni, M. Fattore, F. Maggino, and V. Quondamstefano. 2020. Measuring equitable and sustainable well-being in Italian regions: The non-aggregative approach. *Social Indicators Research* 161(2): 711–733. https://doi.org/10.1007/s11205-020-02388-7.

Alkire, S., and J. Foster. 2011. Counting and multidimensional poverty measurement. *Journal of Public Economics* 95(7–8): 476–487. https://doi.org/10.1016/j.jpubeco.2010.11.006.

Alkire, S., C. Oldiges, and U. Kanagaratnam. 2021. Examining multidimensional poverty reduction in India 2005/6–2015/16: Insights and oversights of the headcount ratio. *World Development* 142: 105454.

Alkire, S., J. E. Foster,S. Seth, M. E. Santos, J. M. Roche, and P. Ballon, (2015). Multidimensional poverty measurement and analysis, Oxford University Press.

Alon, T., M. Doepke, J. Olmstead-Rumsey, and M. Tertilt. 2020. The impact of the coronavirus pandemic on gender equality. *Covid Economics Vetted and Real-Time Papers* 4: 62.

Annoni, P., and R. Brüggemann. 2009. Exploring partial order of European countries. *Social Indicators Research* 92(3): 471–487.

Atkinson, A. B. (1998). Social exclusion, poverty and unemployment. Exclusion, employment and opportunity, *4*.

Augner, C. 2015. Job satisfaction in the European Union. *Journal of Occupational and Environmental Medicine* 57(3): 241–245.

Aum, S., S.Y.T. Lee, and Y. Shin. 2021. Covid-19 doesn't need lockdowns to destroy jobs: The effect of local outbreaks in Korea. *Labour Economics* 70: 101993.

Balde, R., M. Boly, and E. K. Avenyo, (2020). Labour market effects of COVID-19 in sub-Saharan Africa: An informality lens from Burkina Faso, Mali and Senegal. Maastricht Economic and Social Research Institute on Innovation and Technology (UNU-MERIT).

Barnichon, R. 2012. Vacancy posting, job separation and unemployment fluctuations. *Journal of Economic Dynamics and Control* 36(3): 315–330.

Becker, G.S. 2009. *Human capital: A theoretical and empirical analysis, with special reference to education*. University of Chicago Press.

Bjorn, C., M. Lindberg, and D. Rissen. 2016. Significant factors for work attractiveness and how these differ from the current work situation among operating department nurses. *Journal of Clinical Nursing* 25(1–2): 109–116.

Blundell, R., and T. MaCurdy. 1999. Labor supply: A review of alternative approaches. *Handbook of Labor Economics* 3: 1559–1695.

Boniol, M., M. McIsaac, L. Xu, T. Wuliji, K. Diallo and J. Campbell, 2019 Gender equity in the health workforce: analysis of 104 countries (No. WHO/HIS/HWF/Gender/WP1/2019.1). World Health Organization.

Brodeur, A., D. Gray, A. Islam, and S. Bhuiyan. 2020. A literature review of the economics of COVID-19. *Journal of Economic Surveys* 35: 1007.

Brooks, M.G., and J.C. Buckner. 1996. Work and welfare: Job histories, barriers to employment, and predictors of work among low-income single mothers. *American Journal of Orthopsychiatry* 66(4): 526–537.

Bundervoet, T., M.E. Dávalos, and N. Garcia. 2022. The short-term impacts of COVID-19 on households in developing countries: an Overview based on a harmonized dataset of high-frequency surveys. *World Development* 153: 105844.

Burchell, B., K. Sehnbruch, A. Piasna, and N. Agloni. 2014. The quality of employment and decent work: definitions, methodologies, and ongoing debates. *Cambridge Journal of Economics* 38(2): 459–477.

Burchi, F., D. Malerba, C.E. Montenegro, and N. Rippin. 2022. Assessing trends in multidimensional poverty during the MDGs. *Review of Income and Wealth* 68: S317–S346.

Campion, M.A. 1991. Meaning and measurement in turnover. *Journal of Applied Psychology* 76: 199–212.

Chetty, R., J. N. Friedman, N. Hendren, M. Stepner, and The Opportunity Insights Team. 2020. How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data (Vol. 27431). Cambridge, MA: National Bureau of Economic Research.

Coibion, O., Y. Gorodnichenko, and M. Weber, 2020. The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending (No. w27141). National Bureau of Economic Research.

Cowan, B. W. 2020. Short-run effects of COVID-19 on US worker transitions (No. w27315). National Bureau of Economic Research.

Crossley, T.F., P. Fisher, and H. Low. 2021. The heterogeneous and regressive consequences of COVID-19: Evidence from high quality panel data. *Journal of Public Economics* 193: 104334.

Dasgupta, K., and S. Murali. 2020. Pandemic containment and inequality in a developing economy. IIM Bangalore Research Paper, (613).

Davis, S.J., and T. von Wachter. 2011. Recessions and the costs of job loss. *Brookings Papers on Economic Activity* 2: 1–72.

Decancq, K., and M.A. Lugo. 2013. Weights in multidimensional indices of wellbeing: An overview. *Econometric Reviews* 32(1): 7–34.

Dingel, J.I., and B. Neiman. 2020. How many jobs can be done at home? *Journal of Public Economics* 189: 104–235.

Elvira, M.M., and C.D. Zatzick. 2002. Who's displaced first? The role of race in layoff decisions. *Industrial Relations: A Journal of Economy and Society* 41(2): 329–361.

Frederiksen, A. 2008. Gender differences in job separation rates and employment stability: New evidence from employer-employee data. *Labour Economics* 15(5): 915–937.

Garcia-Perez, C., M. Prieto-Alaiz, and H. Simón. 2017. A new multidimensional approach to measuring precarious employment. *Social Indicators Research* 134(2): 437–454.

Giddens, A. 2001. *The global third way debate*. Polity.

Gómez-Salcedo, M.S., L.A. Galvis-Aponte, and V. Royuela. 2017. Quality of work life in Colombia: A multidimensional fuzzy indicator. *Social Indicators Research* 130(3): 911–936.

Gonzalez, P., K. Sehnbruch, M. Apablaza, R. Mendez Pineda, and V. Arriagada. 2021. A multidimensional approach to measuring quality of employment (QoE) deprivation in six central American countries. *Social Indicators Research* 158(1): 107–141.

Griffeth, R.W., and P.W. Hom. 2001. *Retaining Valued Employees*. Sage.

Griffeth, R.W., P.W. Hom, and S. Gaertner. 2000. A meta-analysis of antecedents and correlates of employee turnover: Update, moderator tests, and research implications for the next millennium. *Journal of Management* 26(3): 463–488.

Grimshaw, D., K.G. Ward, J. Rubery, and H. Beynon. 2001. Organisations and the transformation of the internal labour market. *Work, Employment and Society* 15(1): 25–54.

Gunderson, J.M. and J.L. Hotchkiss. 2007. Job separation behavior of WOTC workers: Results from a unique case study. *Social Service Review*, 81(2): 317–342.

Guven, C., P Sotirakopoulos, and A. Ulker. 2020. Short-term labour market effects of COVID-19 and the Associated National Lockdown in Australia: Evidence from longitudinal labour force survey (No. 635). GLO Discussion Paper.

Hagenaars, A. J., K. De Vos, and M. Asghar Zaidi. 1994. Poverty statistics in the late 1980s: Research based on micro-data. Eurostat (European Commission).

Ham, S. 2021. Explaining Gender gaps in the South Korean labor market during the COVID-19 pandemic. *Feminist Economics* 27(1–2): 133–151.

Holtom, B.C., T.R. Mitchell, T.W. Lee, and M.B. Eberly. 2008. 5 turnover and retention research: a glance at the past, a closer review of the present, and a venture into the future. *Academy of Management Annals* 2(1): 231–274.

Hom, P.W., T.R. Mitchell, T.W. Lee, and R.W. Griffeth. 2012. Reviewing employee turnover: focusing on proximal withdrawal states and an expanded criterion. *Psychological Bulletin* 138(5): 831–858.

Huang, A., C. Makridis, M. Baker, M. Medeiros, and Z. Guo. 2020. Understanding the impact of COVID-19 intervention policies on the hospitality labor market. *International Journal of Hospitality Management* 91: 102660.

Huneeus, F., O. Landerretche, E. Puentes, and J. Selman. 2015. A multidimensional employment quality index for Brazil, 2002–11. *International Labour Review* 154(2): 195–226.

International Labour Organization. (2020). Rapid assessment of the employment impact and policy responses of the COVID-19 pandemic on Armenia. October 2020. https://www.ilo.org/wcmsp5/groups/public/---europe/---ro-geneva/---sro-moscow/documents/publication/wcms_762029.pdf

Johnson, C., and B. Williams. 2020. Gender and political leadership in a time of COVID. *Politics and Gender* 16(4): 943–950.

Kalleberg, A.L., B.F. Reskin, and K. Hudson. 2000. Bad jobs in America: Standard and nonstandard employment relations and job quality in the United States. *American Sociological Review* 65(2): 256–278.

Kikuchi, S., S. Kitao, and M. Mikoshiba. 2021. Who suffers from the COVID-19 shocks? Labor market heterogeneity and welfare consequences in Japan. *Journal of the Japanese and International Economies* 59: 101–117.

Kim, M. 2000. Women paid low wages: Who they are and where they work. *Monthly Labor Review* 123: 26–30.

Kim, H. 2019. Beyond monetary poverty analysis: The dynamics of multidimensional child poverty in developing countries. *Social Indicators Research* 141(3): 1107–1136.

Körner, A., M. Reitzle, and R.K. Silbereisen. 2012. Work-related demands and life satisfaction: The effects of engagement and disengagement among employed and long-term unemployed people. *Journal of Vocational Behavior* 80(1): 187–196.

Kulik, L. 2000. Jobless men and women: A comparative analysis of job search intensity, attitudes toward unemployment, and related responses. *Journal of Occupational and Organizational Psychology* 73(4): 487–500.

Kulik, C.T., G. Treuren, and P. Bordia. 2012. Shocks and final straws: Using exit-interview data to examine the unfolding model's decision paths. *Human Resource Management* 51(1): 25–46.

Lay, C.H., and R. Brokenshire. 1997. Conscientiousness, procrastination, and person-task characteristics in job searching by unemployed adults. *Current Psychology* 16(1): 83–96.

Lee, T.W., and T.R. Mitchell. 1994. An alternative approach: The unfolding model of voluntary employee turnover. *Academy of Management Review* 19(1): 51–89.
Lee, T.W., T.R. Mitchell, B.C. Holtom, L.S. McDaniel, and J.W. Hill. 1999. The unfolding model of voluntary turnover: A replication and extension. *Academy of Management Journal* 42: 450–462.
Levy-Garboua, L., C. Montmarquette, and V. Simonnet. 2007. Job satisfaction and quits. *Labour Economics* 14(2): 251–268.
Locke, E.A., D. Sirota, and A.D. Wolfson. 1976. An experimental case study of the successes and failures of job enrichment in a government agency. *Journal of Applied Psychology* 61(6): 701.
Maertz, C.P., Jr., and M.A. Campion. 2004. Profiles in quitting: Integrating process and content turnover theory. *Academy of Management Journal* 47(4): 566–582.
Maertz, C.P., Jr., and K.R. Kmitta. 2012. Integrating turnover reasons and shocks with turnover decision processes. *Journal of Vocational Behavior* 81(1): 26–38.
Maertz, C.P., Jr., M.J. Stevens, and M.A. Campion. 2003. A turnover model for the Mexican maquiladoras. *Journal of Vocational Behavior* 63(1): 111–135.
International Labour Organization. (2020). COVID-19 and the world of work: Impact and policy responses. *ILO Monitor First Edition*, 18 March 2020. https://www.ilo.org/wcmsp5/groups/public/---dgreports/---dcomm/documents/briefingnote/wcms_738753.pdf
Moller, J., and M. Umkehrer. 2015. Are there long-term earnings scars from youth unemployment in Germany? *Jahrbücher Für Nationalökonomie Und Statistik* 235: 474–498.
Montenovo, L., X. Jiang, F. L. Rojas, I. M. Schmutte, K. I. Simon, B. A. Weinberg, and C. Wing, 2020. Determinants of disparities in covid-19 job losses (No. w27132). National Bureau of Economic Research.
Morrell, K., and J. Arnold. 2007. Look after they leap: Illustrating the value of retrospective reports in employee turnover. *The International Journal of Human Resource Management* 18(9): 1683–1699.
Mourdoukoutas, P. 1988. Seasonal employment, seasonal unemployment and unemployment compensation: The case of the tourist industry of the Greek islands. *American Journal of Economics and Sociology* 47(3): 315–329.
National Statistical Service of the Republic of Armenia. 2020. Labor market in Armenia. https://www.armstat.am/file/article/sv_12_20a_141.pdf
National Statistical Service of the Republic of Armenia. 2021. Armenia – Poverty Snapshot over 2009-2020. https://armstat.am/file/article/poverty_2021_e_2..pdf
Nunez, I., and I. Livanos. 2010. Higher education and unemployment in Europe: an analysis of the academic subject and national effects. *Higher Education* 59(4): 475–487.
Olsen, K.M., and A.L. Kalleberg. 2004. Non-standard work in two different employment regimes: Norway and the United States. *Work, Employment and Society* 18(2): 321–348.
Ozughalu, U.M., and F.O. Ogwumike. 2019. Extreme energy poverty incidence and determinants in Nigeria: A multidimensional approach. *Social Indicators Research* 142(3): 997–1014.
Parsons, D.O. 1972. Specific human capital: An application to quit rates and layoff rates. *Journal of Political Economy* 80(6): 1120–1143.
Pham, A.T.Q., P. Mukhopadhaya, and H. Vu. 2020. Targeting administrative regions for multidimensional poverty alleviation: A study on Vietnam. *Social Indicators Research* 150(1): 143–189.
Piasna, A., B. Burchell, and K. Sehnbruch. 2019. Job quality in European employment policy: One step forward, two steps back?. *Transfer: European Review of Labour and Research 25*(2):165-180.
Price, J.L. 1989. The impact of turnover on the organization. *Work and Occupations* 16(4): 461–473.
Reichelt, M., K. Makovi, and A. Sargsyan. 2020. The impact of COVID-19 on gender inequality in the labor market and gender-role attitudes. *European Societies* 23: 1–18.
Rogers, J.K. 1995. Just a temp: Experience and structure of alienation in temporary clerical employment. *Work and Occupations* 22(2): 137–166.
Schmillen, A., and M. Umkehrer. 2013. The scars of youth: Effects of early-career unemployment on future unemployment experience. *International Labour Review* 156(3/4): 465–494.
Schoonbroodt, A. 2018. Parental child care during and outside of typical work hours. *Review of Economics of the Household* 16(2): 453–476.
Sehnbruch, K., B. Burchell, N. Agloni, and A. Piasna. 2015. Human development and decent work: why some concepts succeed and others fail to make an impact. *Development and Change* 46(2): 197–224.
Sehnbruch, K., P. Gonzalez, M. Apablaza, R. Mendez, and V. Arriagada. 2020. The Quality of Employment (QoE) in nine Latin American countries: A multidimensional perspective. *World Development* 127: 104738.

Semmer, N.K., A. Elfering, J. Baillod, M. Berset, and T.A. Beehr. 2014. Push and pull motivations for quitting. *Zeitschrift Für Arbeits-Und Organisationspsychologie a&o.* 58(4): 173–185. https://doi.org/10.1026/0932-4089/a000167.

Sen, A. 2006. Conceptualizing and measuring poverty. In *Poverty and Inequality*, ed. D.B. Grusky and R. Kanbur, 30–46. Stanford University Press.

Sicherman, N. 1996. Gender differences in departures from a large firm. *Industrial and Labor Relations Review* 49(3): 484–505.

Signorelli, M., M. Choudhry, and E. Marelli. 2012. The impact of financial crises on female labour. *The European Journal of Development Research* 24(3): 413–433.

Steel, R.P. 2002. Turnover theory at the empirical interface: Problems of fit and function. *Academy of Management Review*, 27: 346–360.

Stevens, A.H. 1997. Persistent effects of job displacement: The importance of multiple job losses. *Journal of Labor Economics* 15(1): 165–188.

Tverdostup, M. 2022. COVID-19 and gender gaps in employment, wages, and work hours: Lower inequalities and higher motherhood penalty. *Comparative economic studies* 1-23.

United Nations 2015. Transforming our world: The 2030 agenda for sustainable development. A/RES/70/1. New York: United Nations.

Wanberg, C.R. 1997. Antecedents and outcomes of coping behaviors among unemployed and reemployed individuals. *Journal of Applied Psychology* 82(5): 731–744.

Wanberg, C.R., R. Kanfer, and M. Rotundo. 1999. Unemployed individuals: Motives, job-search competencies, and job-search constraints as predictors of job seeking and reemployment. *Journal of Applied Psychology* 84(6): 897–910.

Wanberg, C.R., L.M. Hough, and Z. Song. 2002. Predictive validity of a multidisciplinary model of reemployment success. *Journal of Applied Psychology* 87(6): 1100–1120.

Wanberg, C.R., A.A. Ali, and B. Csillag. 2020. Job seeking: The process and experience of looking for a job. *Annual Review of Organizational Psychology and Organizational Behavior* 7: 315–337.

Westaby, J.D. 2005. Comparing attribute importance and reason methods for understanding behavior: An application to internet job searching. *Applied Psychology* 54(4): 568–583.

World Bank. 2007. Armenia—labor market dynamics. Volume 1. Overview. Washington, DC. https://openknowledge.worldbank.org/handle/10986/7844 License: CC BY 3.0 IGO.

Zavodny, M. 2003. Technology and job separation among young adults, 1980–1998. *Economic Inquiry* 41(2): 264–278.