THE IMPACT OF THE CORONAVIRUS PANDEMIC ON THE LABOR MARKET IN ARMENIA

Knar Khachatryan, PI

Aleksandr Grigoryan, PL

Pundarik Mukhopadhaya, Senior Researcher

Rafayel Avagyan, Assistant

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Executive Summary

This study explores the labor market during COVID-19 pandemics in Armenia. More precisely, we (i) develop indicators capturing deprivation from labor market participation due to COVID-19; (ii) estimate changes in constructed labor market outcome variables for a representative sample of individuals; and (iii) derive policy recommendations for identified deprivation dimensions to the Armenian Government.

Our research brings a number of contributions to the existing evidence that altogether shape a unique study for Armenia. We use a novel empirical method - multidimensional deprivation from the labor market opportunities. We apply the methodology for the Armenian economy to assess the COVID-19 effects, using the 2018 Labor Force Survey (LFS) and the new data collected in November 2020 through Avedisian Center for business research and development (CBRD) at AUA. We investigate the extent of deprivation from labor market opportunities, involving a number of dimensions for both employed and unemployed labor force. Building on that, we further identify the drivers of deprivation by using data on industry type, provinces, urban-rural areas and gender.

We find that labor market conditions have deteriorated in times of COVID-19, resulting in more difficulties in access to labor markets for Armenians. Furthermore, our results show that education is the primary contributor to multidimensional deprivation from labor market outcomes in both 2018 and 2020 data. Unemployment and profession mismatch are among other important factors.

Gender dimension of our analysis shows that pandemic has resulted in a gender gap in terms of the access to labor markets and the appropriation of labor market outcomes. Females are more deprived in terms of lower income and losing jobs. From sectoral analysis, we identify the following patterns. Sectors, vulnerable from the labor market outcome perspectives, such as agriculture and construction, continue to be non-attractive to improve conditions through trainings. Sectors, such as information & communication and service, have the potential to help individuals overcome unfavorable labor conditions.

We relate our recommendations to (but not limited to) the Government of Armenia program for 2019-2023, Employment Strategy for 2019-2023, “Work Armenia” Concept and building on our study key findings we derive four policy briefs.

Chapter 1: Introduction

COVID-19 outbreak generated unprecedented multifaceted crisis for economies all over the world. Policy makers and scholars are exploring the global economic turmoil caused by COVID-19 and are unfolding its impact on different business sectors both in industrialized and developing countries. Businesses are striving to be agile and respond quickly to the current pandemic. Subsequently, like in most countries, unemployment in Armenia rose.

According to the National Statistical Services of the Republic of Armenia[1], the first nine months of 2020 about 47,000 people lost their employment and stable income. The official statistics state that unemployment increased from 17.7% to about 20% in this period. Among the laid off employees only 17% continues seeking actively an employment, about 60% lost hope and is no longer in search for a job. These people or their families have either high intention to emigrate or have already become receivers of social protection pension. The Government aid programs continue supporting those businesses that did not lay off their employees and paid salaries over the pandemic period. Predominantly, services, catering, and construction sectors are affected.

The COVID-19 pandemic has had disparate impacts on different groups of population, mostly explained by the kind of job a person holds, her household and family structure, geographic location, and various measures of socio-economic status. Therefore, the question arises which factors contribute to the deprivation of individuals from employment opportunities and make them more vulnerable to unemployment.

In our study we explore the labor market during COVID-19 crisis in Armenia. In particular, we

(i) develop indicators capturing deprivation from labor market participation due to COVID-19;

(ii) estimate changes in constructed labor market outcome variables for a representative sample of individuals;

(iii) derive policy recommendations for identified deprivation dimensions to the Armenian Government.

[1] See the full report https://www.armstat.am/file/article/sv_12_20a_141.pdf

We investigate the extent of deprivation from labor market opportunities, involving a number of dimensions for both employed and unemployed.[2] In the second part of the analysis, we identify the drivers of deprivation using data on industry type, provinces, urban-rural areas and gender.

Our research brings a number of contributions to the existing literature and evidence that altogether shapes a unique study for Armenia:

(i) *Methodological novelty*: We use a novel empirical method - multidimensional deprivation from the labor market opportunities.

(ii) *Evidence on COVID-19 effects on labor market outcomes from a developing country*. We apply the methodology for the Armenian economy to assess the COVID-19 effect, using the 2018 Labor Force Survey (LFS) and the new data to be collected through Avedisian Center for business research and development (CBRD) at AUA.

(iii) *Conceptual novelty:* We suggest a new conceptual framework in order to investigate on a set of other dimensions of labor market opportunities. Those dimensions allow to study in-depth job related and individual employee level characteristics, such as work status and hours, employment benefits, profession match, training and others. Building on a rigorous conceptual framework of capability approach (Sen, 2006), we, thus, design the multidimensional deprivation from the labor market opportunities.

During recession periods labor markets are significantly hit. Layoffs and furlough are the most common responses to uncertainties and economic crisis. Evidence shows that layoffs and furloughs have occurred on a considerable scale after countries were locked down (Brynjolfsson et al., 2020; Nicola et al., 2020). We have already witnessed different economies having this issue resulting from the multidimensional COVID-19 crisis, whereby men and women are being affected in different ways. For instance, Alon et al. (2020) show that employment opportunities of female workers are likely to be harder hit than those of male employees. The authors claim that the COVID-19 pandemic will have a disproportionate negative effect on women and their employment opportunities. This is an important aspect since the effects of the shock are likely to carry on still for a while after the pandemic. Extent evidence suggests that earnings losses from job losses are highly persistent (Stevens, 1997) and much more severe when they occur in recessions (Davis and von Wachter, 2011). Workers who lose jobs now forgo returns to experience and are likely to have

[2] We elaborate on dimensions in Point 6.

less secure employment in the future (Jarosch, 2015). This situation can affect the wellbeing of individuals and make them deprived from a number of opportunities (education, health, income and others). As a result, current labor market and potential entrants into the job market might become deprived from employment opportunities.

Given the multifaceted nature of employment, we build our study on the capability approach (Sen, 2006), that considers multiple aspects of wellbeing. This means that unemployment is interpreted as a failure of certain basic capabilities. It implies that the ownership allows a person to have opportunities to pursue their goals, but entitlements do not guarantee actual achievements. Personal capabilities are translated into real achievements through several stages that are affected by several internal and external conditions.

We relate our recommendations to (but not limited to) the Government of Armenia program for 2019-2023, Employment Strategy for 2019-2023, "Work Armenia" Concept. The Employment Strategy for 2019-2023 lays down the core vision on employment accessibility and inclusive opportunities for the society at large which is one of the Government priorities. Government policy employment model (Section 5) prioritizes women participation, education linkages to job market, trainings and proportional regional development in terms of labor market development pillars. "Work Armenia" concept sets a more inclusive strategy and action plan for the job market and education alignment, smooth transition and more synergized linkages between education and employment opportunities in Armenia.

Given that in our study we explore a rich set of dimensions which may deprive the active population from employment participation, we contribute to this discourse by providing an evidence-based analysis on the importance of those dimensions and recommendations on how to tackle those issues. Moreover, we have a particular focus on industry, gender and regional effects that shed further light on the importance of those factors for the deprivation from labor market opportunities/participation resulted from COVID-19. This speaks to the distinct objectives of the Government Employment Action plan for 2019-2023 and "Work Armenia" concept.

Policy and program options are derived, and the government can use them to address specific challenges that the labor market is likely to face during the coming crisis. Our findings can generate further development directions for filling the gaps and building a sustainable employment participation model.

Chapter 2: Conceptual framework

The literature on COVID-19 impacts on labor market is evolving rapidly. Montenovo et al. (2020) show that age, gender, race/ethnicity, parental status, and education condition the substantial discrepancies in recent unemployment patterns caused by COVID-19. Furthermore, the authors claim that job attributes are related to employment. Given the specifics of the COVID-19 transmission, employees involved in face-to-face contact might be harder hit than those who can work remotely (Gupta et al., 2020). In addition to this, there are parameters defining higher-risk groups (age, health conditions), thus it is argued that high-risk workers may supply less labor, especially in high-exposure jobs (Guerrieri et al., 2020).

Early evidence on the pandemic impact on the gender aspect of the labor market shows that in the short-run female employment opportunities are likely to be more strongly affected than those of male (Alon et al., 2020). To certain extent this is explained by the gender composition of different sectors of the economy. Provided that job loss during a recession has durable and negative effects on future earnings and job security (Davis and von Wachter 2011, Jarosch 2015), the crisis effects may persist and contribute to the average gender wage gap for years to come. Another important fact that can play a role on the labor supply is related to the shutdown of childcare, schooling, home, and family health care services (Dingel and Neiman, 2020). Concerned work force might be exposed to reduce the labor supply given those constraints. Particularly, single parents, who are disproportionately female, are most likely to have lost jobs (Montenovo et al., 2020). This is in line with Alon et al. (2020) that claim that the impact of the pandemics on working mothers could be persistent. Evidence from a developing economy suggests that the COVID-19 unequal impact on the labor market is due to the workers' skills (high vs low) (Dasgupta and Murali, 2020).

Exploring further the pandemic's uneven effect on the labor market in the US, UK and Germany, Adams-Prassl et al. (2020) find that within countries, workers in less remote-workable occupations, less educated workers and women are more affected by the crisis. Interestingly, the authors suggest that more flexible unemployment insurance systems (such as in Germany) that allow workers to temporarily reduce worker hours without severing employment relationships, enable to address more efficiently the crisis than countries with more conventional unemployment insurance systems. In terms of the remote work, younger people and female employees are more likely to undertake it (Brynjolfsson et al., 2020).

Earlier studies on layoff decisions (such as Elvira and Zatzick, 2002) show that an employee's age has a negative and significant effect on layoff chances. Education level is an effective tool to reduce unemployment (Nunez and Livanos, 2010; Tansel and Tasci, 2004). Additionally, employees in higher salary quartiles are significantly less likely to be laid off than employees in the lowest salary quartiles. Incentive pay (such as bonuses, rewards) are negatively associated with layoff chances. Partially, this can be explained by the fact that incentive pay is based on performance evaluations.

Theories of quitting (Locke et al., 1976; Price, 1989) indicate employees who are dissatisfied with their excessive load are most likely to volunteer for layoff. This leads to the claim that low-paid and less educated employees with little prospect of being promoted are likely to volunteer. On the other hand, employees with dependants are less likely to volunteer than others.

The evidence posits 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 (Manzoni and Mooi-Reci, 2011; Schmillen and Umkehrer, 2013; Moller and Umkehrer, 2015). This implies that incumbent and experienced workforce disposes certain market power due to their accumulated know-how, skills, initial training costs invested by the employer and possible layoff restrictions. Since factors that typically determine layoffs include seniority and performance (Thurow, 1975; Reagan, 1992) more experienced labor is assumed to be exposed to less chances of layoff. Furthermore, the long-lasting effects of economic crises can be expressed by negative implications on well-being as a result of involuntary unemployment (Hetschko et al., 2019), working-life expectancy, in particular for older workers (Dudel and Myrskylä, 2017), on fertility (Seltzer, 2019). One of the most decisive factors with respect to the material impact of unemployment is the position of the unemployed in the household (Bison and Esping-Andersen, 2000).

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, at an individual level unemployment can result in social deprivation that leads to a decline in self-respect, social isolation, and further negative effects on life prospects (Oswald, 1994). Unemployment can derive to individuals' marginalization, that is to say exclusion from labour market competition.

Deprivation from the labor market can become costlier when coupled with increasing labour mismatch. Geographical space (urban or rural areas) can be decisive in terms of

employment opportunities because unemployment is rooted in deeper structural factors such as insufficient infrastructure, dysfunctional industries of the region (from the demand side) as well as a surplus of non-qualified or highly specialized labour (from the supply side).
People without qualifications are much more vulnerable to losing a job and are more prone to be trapped in an unemployment trap than those with higher qualification levels (Giddens, 2001).

Government strategies should be addressed at creating new employment opportunities for deprived labor market, creating accessible opportunities for them to be equipped with new skills needed in emerging trends, encouraging private investments, and minimize the mismatch between the outputs of educational systems and the labor market needs. Designing policies that are targeted at the most vulnerable subgroups mostly hit by the COVID-19 crisis will contribute to soften devastating and long-term effects caused by deprivation from labor market opportunities.

Chapter 3: Methodology

We develop measures for multidimensional deprivation from labor market outcomes (opportunities) based on Alkire-Foster dual cut-off methodology (Alkire and Foster, 2008). Multidimensional deprivation indexes, namely, adjusted headcount ratio, censored headcount ratio and average intensity will be constructed from the following datasets: (i) 2018 Labor Force Survey and (ii) a new survey conducted by CBRD.

Our comparative analysis consists of two major parts: We compare deprivation indexes and contributions to the one of the indices, censored headcount ratio, for the two datasets and make judgements on labor market conditions and structural changes. This analysis is particularly aimed to identify changes in indicators of labor market outcomes resulted from COVID-19. From the contribution analysis, we identify those indicators which capture the deprivation from labor market opportunities the most. The map from a distinct indicator to the overall deprivation score in terms of an absolute magnitude and relative contribution will be identified.

We also conduct regression analysis for further exploring regional, gender and industry effects on the deprivation score. Industrial analysis in the context of labor market outcomes is typically one-dimensional. Regional disproportionalities in labor market performance due to COVID-19 will be identified by controlling for provinces (marzes) and urban-rural areas. Gender imbalance dynamics due to COVID-19 is another major issue, to be explored carefully within our study.

Application of Alkire-Foster methodology in the context of labor market outcomes is discussed next.

3.1 Method

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 $i = 1, 2, \dots, n$, and $j = 1, 2, \dots, d$. We use a dual cut-off framework by Alkire and Foster (2008), 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,

$$c_i = \sum_{j=1}^{d} w_j g_{ij}. \qquad (1)$$

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 as $c_i(k)$), otherwise (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:

$$H = \frac{q}{n}, \tag{2}$$

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,

$$A = \frac{\sum_{i=1}^{n} c_i(k)}{q}. \tag{3}$$

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:

$$M_0 = H \times A = \frac{q}{n} . \frac{\sum_{i=1}^{n} c_i(k)}{q} = \frac{\sum_{i=1}^{n} c_i(k)}{n} = \frac{\sum_{i=1}^{n} \sum_{j}^{k} g_{ij}(k)}{n}. \tag{4}$$

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 “poor” 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:

$$H_j^c = \frac{\sum_{i=1}^{n} g_{ij}(k)}{w_j n}. \tag{5}$$

The adjusted headcount ratio M_0 satisfies the additive decomposability principle (see Alkire and Foster, 2008), 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:

$$M_0 = \sum_{j=1}^{k} w_j H_j^C. \tag{6}$$

The contribution of dimension j is

$$C_j = \frac{w_j H_j^C}{M_0}. \tag{7}$$

3.2 Dimensions and Indicators

In Table 1, we list dimensions and indicators, which are used for constructing multidimensional poverty measurements. *Income, education, employment status, child and elderly care and profession match* stand as distinct dimensions, represented by single indicators. We have two dimensions, namely, *job status* and *no-job status*, constituting a number of indicators. For the *job status*, we have 7 indicators, which aims to capture deprivation for individuals who have a job. Importantly, individuals, who do not have a job, they are not deprived in these indicators, since we have a distinct dimension, employment status, capturing deprivation from holding *no-job status*. Within *no-job status*, on the other hand, we have 3 indicators, and individuals as unemployed might be further deprived on these 3 indicators.

Table 1. Dimensions and indicators

Dimension	*Indicator*	*Deprived if, …*	*Weight* *Dim.*	*Weight* *Ind.*
Income	Income (level or groups)	income is up to 55,000 AMD	1/7	1/7
Education	Education (years or level)	less than bachelor	1/7	1/7
Employment status	Employed, looking for a job; does not look for a job	Did not have any job and was looking for one (unemployed)	1/7	1/7
Job status	What benefits, guarantees do you receive / can you receive at your working place?	None of them	1/7	1/49
	Job status (contract)	Employee with a verbal agreement		1/49
	Contract length	Up to 3 months		1/49
	Full time / overtime / part time	Part-time		1/49
	Working hours	Day and night (all day) or …?		1/49
	Labor union	if the answer is not YES.		1/49
	Changing the work	Yes		1/49
Care	Why do you personally take care of your child or your family sick / disabled / old member?	Impossible to cover costs or There is no relevant institution care services in the area	1/7	1/7
Profession match	Profession match	Not useful Do not get profession Do not know / difficult to answer	1/7	1/7

No job	Quitting the job	Either of the following categories: self-reduction, illness, childcare, care of family sick, end of temporary work, illness, low wage	1/7	1/21
	Reasons not looking for a job	Illness, lack of relevant skills / work experience, considered too young / too old to find a job, lack of jobs in the area, family / spouse does not allow, no hope to find a suitable job, do not know where and how to look for a job		1/21
	Offer refused	If the answer was not "did not refuse"		1/21

To decide on the weights for the dimensions and indicators we follow MPI's normative weights (see Decancq and Lugo, 2013), Each dimension is given equal weight (1/7), and within a dimension, indicators are given equal weights. In Table 1, we report weights for each dimension and indicator.

Chapter 4: Data

We use two datasets, CBRD dataset collected in November 2020 and Labor Force Survey (LFS) 2018. The CBRD survey was conducted by filling out a questionnaire through an online platform. The potential respondents got an invitation to participate in an online survey through SMS messages. Respondents were chosen through territorially stratified random sampling, from Yerevan and all other regions of the country. The survey was conducted by mobile online version in the period of 15-19 November 2020. 3,202 respondents came from Yerevan and both urban and rural locations from the all regions of RA.

Regarding the LFS from 2018, we retrieve 19,467 observations, available for constructing multidimensional deprivation measures. Further inspection of the two datasets, we observe high difference in the proportions of education categories. The cut-off of deprivation from education is taken the level of education less than bachelor. From Table A1, Appendix, we learn that only 1/3 of respondents do not have a bachelor's degree. The corresponding fraction in the LFS survey is 0.79 (Table 2).

Given that LFS survey is more representative, based on face to face interview, we think that it is CBRD survey that suffers in self-selection bias. The online platform, required for CBRD survey, is more likely to be used by respondents with higher education, and this is the potential source of bias. In order to take account for this bias, we randomly draw a sub-sample from LFS with proportions of the deprivation form the level of education dimension (bachelor) observed from CBRD dataset. The sub-sample size is taken the same as the one in CBRD dataset.

Table 2. Deprivation measures from CBRD 2020 and LFS 2018 full datasets

	LFS data		*CBRD data*			
Dimensions/indicators	*Mean*	*St. dev.*	*Mean*	*St. dev.*	*Min.*	*Max.*
Income	0.0071	0.0839	0.1992	0.3995	0	1
Education	0.7898	0.4075	0.3398	0.4738	0	1
Employment status	0.0133	0.1144	0.2509	0.4337	0	1
Employment benefits	0.7122	0.4528	0.3556	0.4789	0	1
Contract	0.0007	0.0258	0.0627	0.2425	0	1
Contract duration	0.0184	0.1345	0.0724	0.2592	0	1
Work time	0.0915	0.2884	0.1420	0.3491	0	1
Working hours	0.0138	0.1167	0.1571	0.3641	0	1
Union	0.3819	0.4859	0.5403	0.4985	0	1
Work change	0.1274	0.3334	0.5093	0.5001	0	1
Child/elderly care	0.0055	0.0743	0.1571	0.3641	0	1
Profession match	0.5743	0.4945	0.1964	0.3974	0	1
Reasons for quitting work	0.0714	0.2575	0.3060	0.4610	0	1
Work search	0.3125	0.4635	0.0848	0.2786	0	1
Offer refused	0.0171	0.1297	0.4163	0.4931	0	1
Number of observations	19,467		1,451			

Note: Minimum and maximum values correspond to “non-deprived” and “deprives” statuses, respectively.

In Table 2, we report the mean and standard deviations of (binary) deprivation scores, calculated for indicators. For the LFS data, all observations are used to calculate deprivation scores. In Table 3, we report the same statistics, but the random sub-sample is used for the LFS data. Throughout this paper, we use the sub-sample for LFS dataset, unless otherwise is indicated.

Table 3. Deprivation measures from CBRD 2020 and LFS 2018 subsample datasets

	LFS data		*CBRD data*			
Variables	*Mean*	*St. dev.*	*Mean*	*St. dev.*	*Min.*	*Max.*
Income	0.0069	0.0828	0.1992	0.3995	0	1
Education	0.3398	0.4738	0.3398	0.4738	0	1
Employment status	0.0124	0.1107	0.2509	0.4337	0	1
Employment benefits	0.5768	0.4942	0.3556	0.4789	0	1
Contract	0.0014	0.0371	0.0627	0.2425	0	1
Contract duration	0.0138	0.1166	0.0724	0.2592	0	1
Work time	0.0986	0.2982	0.1420	0.3491	0	1
Working hours	0.0186	0.1352	0.1571	0.3641	0	1
Union	0.4149	0.4929	0.5403	0.4985	0	1
Work change	0.1427	0.3498	0.5093	0.5001	0	1
Child/elderly care	0.0034	0.0586	0.1571	0.3641	0	1
Profession match	0.3150	0.4647	0.1964	0.3974	0	1
Reasons for quitting work	0.0558	0.2297	0.3060	0.4610	0	1
Work search	0.2412	0.4280	0.0848	0.2786	0	1
Offer refused	0.0221	0.1469	0.4163	0.4931	0	1
Number of observations	1,451		1,451			

Note: Minimum and maximum values correspond to "non-deprived" and "deprives" statuses, respectively.

Going through indicators and dimensions, we observe a systematic positive difference between the mean values of deprivation scores calculated from CBRD and LFS datasets. Large differences are particularly observed for income, employment status, work time, working hours, work change, care, reasons for quitting job and offer refused. There is only one indicator (and no dimension), for which the proportion of deprived individuals is larger for LFS data, which is employment benefits. This is immediate evidence that deprivation from labor market outcomes are larger during COVID-19 (and the post-war period), compared to 2018.

Next, we calculate multidimensional deprivation measurements using the two dataset and conduct comparative analysis.

Chapter 5: Multidimensional deprivation analysis

5.1 Estimates of multidimensional deprivation

Table 3 shows the estimates of multidimensional deprivation including the censored headcount ratio (H), average intensity of deprivations (A) and adjusted headcount ratio (M0), calculated from

LFS and CBRD dataset. We estimate multidimensional deprivation measurements for cut-off values 0.1-0.9. With the increase in the poverty cut-off value (*k*), the proportion of the population defined as deprived (*H*) decreases, as fewer individuals are deprived in 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.

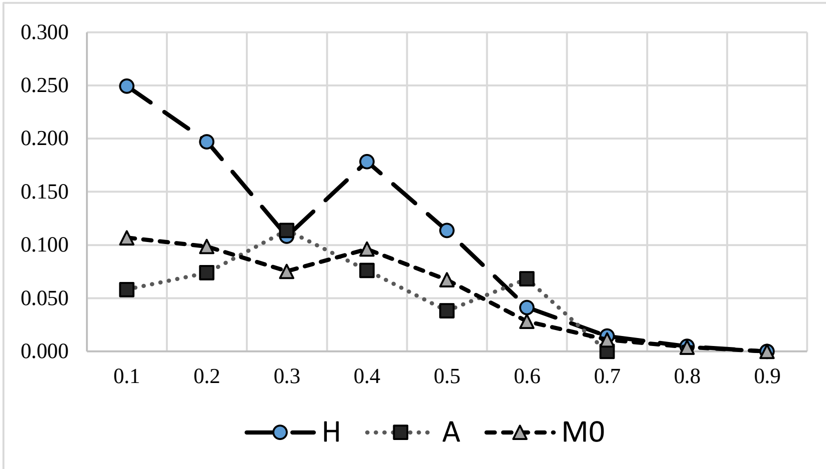
Table 4. Multidimensional deprivation indexes calculated from LFS and CBRD dataset

k	*H (headcount ratio)*			*A (average intensity of deprivation)*			*M0 (adjusted headcount ratio)*		
	LFS	*CBRD*	*Diff.*	*LFS*	*CBRD*	*Diff.*	*LFS*	*CBRD*	*Diff.*
0.1	0.447	0.696	0.249	0.266	0.324	0.058	0.119	0.226	0.107
0.2	0.327	0.524	0.197	0.304	0.378	0.074	0.099	0.198	0.099
0.3	0.230	0.338	0.108	0.340	0.454	0.114	0.078	0.154	0.075
0.4	0.012	0.191	0.178	0.458	0.534	0.076	0.006	0.102	0.096
0.5	0.003	0.116	0.114	0.553	0.591	0.038	0.002	0.069	0.067
0.6	0.001	0.042	0.041	0.612	0.680	0.068	0.000	0.029	0.028
0.7	0.000	0.014	0.014				0.000	0.011	0.011
0.8	0.000	0.005	0.005				0.000	0.004	0.004
0.9	0.000	0.000	0.000				0.000	0.000	0.000

Note: Differences for cut-offs 0.1 – 0.6 are significant at the 1 percent level.

In Table 4, deprivation indexes are calculated for LFS and CBRD datasets, and the third column for each index is the difference between CBRD dataset and LFS measures, calculated for each cut-off. For a given cut-off, all 3 indexes are higher for CBRD dataset. That is, on average, individuals representing labor force in the country, are more exposed to (multidimensional) deprivation from labor markets outcomes in 2020, compared to 2018. The proportion of deprived drastically decays from k = 0.4 to k=0.3 for the case of LFS. In fact, there are only few individuals that are deprived in dimensions/indicators with summarized weights exceeding 0.4. The dramatic decay is both reflected in H and M0 indexes. Concerning the average intensity index, increasing in cut-off, individuals experiencing simultaneous deprivations in a higher fraction of dimensions are more in 2020 than in 2018, indicating that excessive deprivation is not only reflected in headcount and censored ratios, but also in intensity.

Figure 1. Differences in multidimensional deprivation measurements, calculated for LFS and CBRD datasets.



In Figure 1, we plot the differences in deprivation measurements between 2020 (CBRD dataset) and 2018 (LFS) against cut-off values. For the headcount ratio (H), the difference is the largest for k=0.1. It decays until k=0.3 and jumps at k=0.4. After, it continues decaying. For the adjusted headcount ratio (M0), the difference is the largest at k = 0.1 and decays almost uniformly. The second highest pick is at k =0.4, but it is not as vivid as in the case of the headcount ratio. The difference in average intensity deprivation is the largest at k=0.3, indicating that when the two measurements from 2020 and 2018 get closer, the difference in terms of the deprivation intensity (simultaneous deprivation from many dimensions/indicators) increases. That is, even when deprivation from labor market outcomes in 2020 becomes compatible to its counterpart in 2018, deprivation intensities differ even more.

Overall, we conclude that multidimensional deprivation from labor market outcomes is systematically larger in 2020. All 3 measurements suggest that labor market conditions deteriorated in 2020, making residents in Armenia more exposed to deprivation from labor outcomes and hence poverty.

5.2 Contributions analysis

We report contributions of dimensions and indicators to the adjusted headcount ratio M0 in Table 5, for cut-off value 0.3. Equation (7) implies that if the contribution is larger than the weight in one dimension/indicator, individuals with deprivation status are deprived more in that dimension/indicator. In Table 5, for both datasets, education contributes to multidimensional deprivation from labor market outcomes most. The second highest contributor differs in 2018 and 2020. In 2018, profession match is the second highest contributor, 0.411, which is little less than the contribution of education (0.416). In 2020, the second highest contributor is the employment status – unemployment contributed to M0 by 19 percent, while its contribution in 2018 was only 1.4 percent. Contribution of profession match in 2020 falls below its weight, suggesting that high deprivation observed in times of pandemic cannot be explained by skill mismatch in the labor market. Interestingly, neither *job status* nor *no-job status* does not have significant contribution to the adjusted headcount ratio, suggesting that indicators within these dimensions do not play a critical role in explaining deprivation from labor market outcomes.

Table 5. Contributions analysis for k=3

Dimension	*Weight*	*Contribution*			*Indicators*	*Weight*	*Contribution*	
		LFS	*CBRD*				*LFS*	*CBRD*
Income	0.143	0.008	0.154	1	Income	0.143	0.008	0.154
Education	0.143	0.416	0.209	2	Education	0.143	0.416	0.209
Employment status	0.143	0.014	0.190	3	Employment status	0.143	0.014	0.19
Job status	0.143	0.088	0.086	4	Employment benefits	0.020	0.051	0.033
				5	Contract	0.020	0.000	0.002
				6	Contract duration	0.020	0.001	0.002
				7	Work time	0.020	0.006	0.004
				8	Working hours	0.020	0.001	0.004
				9	Union	0.020	0.022	0.011
				10	Work change	0.020	0.007	0.03
Child/elderly care	0.143	0.005	0.098	11	Child/elderly care	0.143	0.005	0.098
Profession match	0.143	0.411	0.137	12	Profession match	0.143	0.411	0.137
"No job" status	0.143	0.057	0.125	13	Reasons for quitting work	0.048	0.009	0.057
				14	Work search	0.048	0.045	0.016
				15	Offer refused	0.048	0.003	0.052

Contribution analysis shows that even selecting a sub-sample from LFS, biased towards higher education, education continues to be the main contributor of multidimensional deprivation. In the sub-sample, 1/3 of individuals are deprived from education, the latter standing as a distinct dimension. Given that all other dimensions/indicators have much smaller or negligible contribution, except profession match, contribution of education (as well as profession match) turns to be very high. The picture is different in 2020. Low income and high unemployment are among the contributors, which deprives the contribution of education and make the contribution of profession match lower than its weight. High unemployment in 2020 increases the potential contribution power of *no-job* status, which turns to be closer to its weight, 0.125. *Reasons for quitting work* and *offer refused* are the indicators, which contribute more than their weights do. That is, in 2020, unemployed residents are excessively deprived from labor market outcomes due to reasons resulting in a job quit and/or refusing offers.

5.3 Regional Analysis

Regional dimension of deprivation analysis involves regional variation of the 3 multidimensional deprivation indexes, H, A and M0. In Table 6 we report for indexes, calculated from LFS (sub-sample) and CBRD data, for the capital and 10 provinces. In the case of LFS, the highest proportion of deprived (H) is observed in Aragatsotn, 0.474. The highest M0 is observed in the same province. In Aragatsotn, the highest proportion of respondents deprived in profession match and the second highest proportion deprived in education are observed (61 percent and 47 percent respectively). Agriculture is the dominant sector in this province, and labor market infrastructures are not properly functioning in that sector. From CBRD data, the highest H and M0 are observed for Shirak. Unemployment in Shirak is traditionally high and pandemic made the situation even worse. According to the data, Shirak has the highest unemployment rate, 35 percent, among provinces and the capital. The second highest unemployment rate is observed in Kotayq, which has a high share of manufacturing in the industry structure, and the negative effect of pandemic is reflected in the high rate of unemployment in that sector. Shirak is the second in the proportion of respondents, deprived in income dimension, 32 percent, while the highest proportion is observed in Gegharquniq province, 33 percent. In all provinces, except Aragatsotn, headcount and adjusted headcount ratios, as well as average intensity of deprivation are larger in 2020. Differences is significant at the 1 percent level.

Regarding the capital, the headcount and adjusted headcount ratios are the lowest in 2018, 0.124 and 0.041, respectively. In 2020, the picture is significantly different – deprivation indexes are close to country level indexes, suggesting that pandemic affected labor market outcomes in Yerevan more intensively.

Table 6. Multidimensional deprivation measurements for provinces, k = 0.3

	H (headcount ratio)			*A (average intensity of deprivation)*			*M0 (adjusted headcount ratio)*		
Provinces	*LFS*	*CBRD*	*Diff*	*LFS*	*CBRD*	*Diff*	*LFS*	*CBRD*	*Diff*
Yerevan	0.124	0.326	0.202	0.333	0.443	0.110	0.041	0.145	0.103
Aragatsotn	0.474	0.333	-0.140	0.345	0.456	0.111	0.164	0.152	-0.012
Ararat	0.338	0.367	0.030	0.345	0.459	0.114	0.116	0.169	0.052
Armavir	0.257	0.337	0.080	0.342	0.480	0.138	0.088	0.162	0.074
Gegharquniq	0.265	0.386	0.120	0.353	0.470	0.117	0.094	0.181	0.088
Kotayq	0.242	0.403	0.161	0.339	0.470	0.131	0.082	0.189	0.107
Lori	0.241	0.355	0.114	0.336	0.495	0.159	0.081	0.176	0.095
Shirak	0.264	0.435	0.172	0.341	0.465	0.125	0.090	0.203	0.113
Syunik	0.179	0.189	0.009	0.321	0.467	0.147	0.058	0.088	0.031
Tavush	0.262	0.266	0.004	0.349	0.440	0.091	0.091	0.117	0.026
Vayots Dzor	0.186	0.333	0.148	0.317	0.469	0.153	0.059	0.156	0.098

Note: Differences are significant (at the 1 percent level), except for the headcount ratio for Syunik and Tavush provinces.

5.4 Gender analysis

Next, we explore gender differences in labor market outcomes. We report H, M0 and A indexes for CBRD and LFS datasets separately, Table 6 and 7, respectively, for cut-off values 0.1 – 0.9. From the previous analysis we already know that, in 2018, there are few individuals deprived from labor market outcomes for cut-offs higher than 0.3. However, it is interesting to observe gender differences in deprivation (if any) for higher cut-offs too.

There is a substantial variation in both levels of and differences in deprivation. From 2020 data, we observe high proportions deprived in terms of H and M0, as well high deprivation intensity (A). Headcount and adjusted headcount ratios decay in cut-off rather gradually, suggesting that deprivation is uniformly spread and refers to large layers of society, both males and females. Deprivation is, however, systematically high among females. The gap is observed for all measurements and cut-off values. Differences are significant at the 1 percent level.

Table 7. Multidimensional deprivation measurements calculated from CBRD dataset

k	*H (headcount ratio)*			*A (average intensity of deprivation)*			*M0 (adjusted headcount ratio)*		
	Male	*Female*	*Diff.*	*Male*	*Female*	*Diff.*	*Male*	*Female*	*Diff.*
0.1	0.640	0.724	0.084	0.309	0.340	0.031	0.198	0.247	0.048
0.2	0.442	0.567	0.125	0.375	0.391	0.016	0.166	0.222	0.056
0.3	0.279	0.389	0.110	0.452	0.462	0.010	0.126	0.180	0.054
0.4	0.154	0.227	0.073	0.537	0.544	0.007	0.083	0.123	0.041
0.5	0.092	0.143	0.051	0.591	0.603	0.012	0.055	0.086	0.032

0.6	0.037	0.058	0.022	0.672	0.689	0.016	0.025	0.040	0.016
0.7	0.013	0.020	0.007	0.738	0.774	0.036	0.010	0.016	0.006
0.8	0.002	0.009	0.008	0.830	0.836	0.006	0.002	0.008	0.006
0.9	0.000	0.000	0.000				0.000	0.000	0.000

Note: Differences for cut-offs 0.1 – 0.6 are significant at the 1 percent level.

Regarding the 2018 data, deprivation collapses to almost null at the k = 0.4, as expected. More interestingly, there is no systematic gender gap in deprivation from labor market outcomes. The difference in headcount ratios for k = 0.1 is negative, indicating that females are less deprived from labor market outcomes than male for the lowest level of cut-off under consideration. The sign changes for higher cut-offs, but the difference is not significant.

Table 8. Multidimensional deprivation measurements calculated from LFS dataset

k	*H (headcount ratio)*			*A (average intensity of deprivation)*			*M0 (adjusted headcount ratio)*		
	Male	*Female*	*Diff.*	*Male*	*Female*	*Diff.*	*Male*	*Female*	*Diff.*
0.1	0.454	0.441	-0.013	0.262	0.270	0.008	0.119	0.119	0.000
0.2	0.320	0.333	0.013	0.302	0.306	0.004	0.097	0.102	0.005
0.3	0.226	0.234	0.008	0.338	0.342	0.004	0.076	0.080	0.004
0.4	0.013	0.011	-0.002	0.441	0.474	0.033	0.006	0.005	0.000
0.5	0.001	0.004	0.002	0.510	0.567	0.057	0.001	0.002	0.001
0.6	0.000	0.001	0.001		0.612		0.000	0.001	0.001
0.7	0.000	0.000	0.000				0.000	0.000	0.000
0.8	0.000	0.000	0.000				0.000	0.000	0.000
0.9	0.000	0.000	0.000				0.000	0.000	0.000

Note: Differences are not significant at any conventional level.

Our conclusion from gender analysis is that pandemic has resulted in gender gap in access to labor market and the appropriation of labor market outcomes. Females are more systematically deprived from labor outcomes, in terms of lower income (31 percent of deprived cases for female and 13.59 percent of deprived cases for males) losing jobs (29 percent for females versus 26 percent for males) and more.

Our finding is in line with exiting evidence on the pandemic impact on the gender aspect of the labor market that show female employment opportunities are likely to be more strongly affected than those of male (Alon et al. 2020). To certain extent this is explained by the gender composition of different sectors of the economy. Also, the concerned workface might face employment challenges due to the shutdown of childcare, schooling, home and family health care services (Dingel and Neiman, 2020).

5.5 Sectoral Analysis

We analyze the sectoral dimension of the deprivation form labor outcomes in the following way. Firstly, we construct multidimensional deprivation indexes for sectors (economic areas) based on NACE classification. Secondly, we construct these indexes for consolidated areas, in which respondents from CBRD dataset took training(s). As we are not comparing outcomes on the same variables from the two datasets, we use a larger subsample from LFS dataset (6000 observation), to obtain more reliable statistics for 21 sectors.

From Table 8 we observe that the highest headcount ratio (H) is observed for the sector agriculture, forestry and fishing (sector A), 0.517. Consequently, adjusted headcount ratio (M0) is also the largest for this category, 0.186. Average intensity of deprivation (A) is one of the highest, 0.350, suggesting that among deprived individuals in sector A, many of them are deprived in several (many) dimensions. We conclude that, in regular times, individuals, engaged in agricultural and related sectoral activities, are exposed to multidimensional deprivation from labor market outcomes most. Contribution to adjusted headcount ratio is the highest for education and profession (skill) mismatch dimensions. Whether such individuals see training as an instrument to mitigate the vulnerability towards labor market outcomes or conditions, can be observed from Table 9. Those respondents, who took training in the area of agriculture are deprived from labor market outcomes most. However, there are only few individuals (8) who took trainings in the area of agriculture.

Table 9. Multidimensional deprivation measurements calculated for economic sectors (NACE) using LFS dataset, for k = 0.3

Economic area (NACE classification)		*H (headcount ratio)*	*A (average intensity of deprivation)*	*M0 (adjusted headcount ratio)*
A	*Agriculture, Forestry and Fishing*	0.5169	0.3492	0.1805
B	*Mining and Quarrying*	0.0435	0.3061	0.0133
C	*Manufacturing*	0.1804	0.3194	0.0576
D	*Electricity, Gas, Steam and Air Conditioning Supply*	0.0550	0.3095	0.0170
E	*Water Supply; Sewerage, Waste Management and Remediation Activities*	0.1875	0.3129	0.0587
F	*Construction*	0.3370	0.3502	0.1180
G	*Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles*	0.2128	0.3298	0.0702
H	*Transportation and Storage*	0.1825	0.3398	0.0620
I	*Accommodation and Food Service Activities*	0.2895	0.3265	0.0945
J	*Information and Communication*	0.0189	0.3367	0.0064

K	*Financial and Insurance Activities*	0.0000		0.0000
L	*Real Estate Activities*	0.0000		0.0000
M	*Professional, Scientific and Technical Activities*	0.0411	0.3333	0.0137
N	*Administrative and Support Service Activities*	0.0952	0.3776	0.0360
O	*Public Administration and Defense; Compulsory Social Security*	0.0705	0.3148	0.0222
P	*Education*	0.0164	0.3180	0.0052
Q	*Human Health and Social Work Activities*	0.0365	0.3236	0.0118
R	*Arts, Entertainment and Recreation*	0.0455	0.3061	0.0139
S	*Other Service Activities*	0.0980	0.3796	0.0372
T	*Activities of Households as Employers; Non-differentiate Goods and Services Producing Activities of Households for Own Use*	0.0000		0.0000
U	*Activities of Extraterritorial Organizations and Bodies*	0.1667	0.3061	0.0510

Note: Number of observations is 6000.

The second most vulnerable sector in 2018 was construction. This sector did not fully recover after the global crisis 2008 – 2014. However, it continues to be one of the leading sectors of the Armenian economy. Skill miss-match is the reason driving such a high deprivation in the sector. From CBRD data, we have only 3 individuals who took in training(s) in the area of construction, suggesting that trainings may not be efficient to improve skills in construction.[3] Further and more detailed analysis are needed to understand the reasons why only few individuals are taking trainings in areas, which are particularly vulnerable to education and skill mismatch. Individuals working in sectors such as information and communication (J), financial and insurance activities (K) and education (P) are not deprived or their deprivation is negligible. In 2018, these sectors have been considered as attractive from the labor market outcomes perspective. The only dimension that individuals in these sectors might be systematically deprived is education.

From Table 3, we learn that respondents taking trainings in the area of information and communication are highly deprived. Participation rate of such training is quite high, 17 percent of 1051 individuals, who took at least one training. 44 percent of respondents, taking training(s) in this area, are deprived. Intensity of deprivation is also high, 47 percent. This result, together with the observation from 2018 data, suggests that many individuals consider skills and knowledge in the information and communication sector are instrumental to get rid of deprivation from labor market outcomes, may it be income, unemployment or education.

Similar pattern is observed in the area of services. From the 2018 data, we observe that individuals engaged in service sectors are deprived less (sectors R and S), except accommodation

[3] These observations are relegated to the "other" category.

and food service activities (I) in which deprivation is moderate. From the 2020 data, high deprivation is observed among individuals who take trainings in the area service. Similar to information and communication sector, service seems to be considered as a sector which can help drastically improve labor market conditions form individuals taking training in this area.

Interestingly, individuals taking training in the area of financial and insurance activities, education and management, pattern relatively low deprivation. The fraction of respondents taking trainings in these areas are relatively high, suggesting that demand for such training is high. We can conclude that participants in trainings from these areas aim to further improve their skills and knowledge and not considering training opportunities to get out of the deprivation trap.

Table 10. Multidimensional deprivation measurements calculated for areas of trainings (CBRD dataset) for cut-off 0.3

Area/Sector	*H (headcount ratio)*	*A (average intensity of deprivation)*	*M0 (adjusted headcount ratio)*	*Frequency (%)*
Financial and insurance	0.231	0.440	0.101	9.900
Agriculture	0.625	0.473	0.296	0.760
Manufacturing	0.300	0.465	0.139	2.850
Service	0.566	0.488	0.276	16.650
Information and communication	0.444	0.471	0.210	14.560
Education	0.200	0.469	0.094	5.230
Public sector	0.207	0.463	0.096	2.760
Management	0.176	0.469	0.083	4.850
Other	0.316	0.431	0.136	42.440

Overall, we identify 3 patterns from the sectoral analysis. Sectors which are vulnerable from the labor market outcome perspectives, such as agriculture and construction, continue to be non-attractive for individuals and/or training organization to improve conditions through trainings. There are sectors, which can “rescue” individuals from current unfavorable labor related conditions. These sectors enable labor force, previously not successful in the market, to catch-up making systematic learning efforts. These are information and communication and, at least to some extent, services. Finally, there are a number of sectors, in which training can help further improve skills and knowledge and acquire better conditions labor markets.

Chapter 6: Regression analysis

In this section we use the regression analysis, following Alkire et al. (2015), to estimate the relationship between multidimensional deprivation from labor market outcomes and individual, spatial and sectoral factors. The binary deprivation score of multidimensional deprivation is considered as the 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

$$Prob(X_i) = G(X_i\beta), \quad (8)$$

where the function $G(.)$ is probability distribution. In case $G(.)$ is a normal probability distribution function, we estimate the probit model. Alternatively, G(.) can be a logistic function, in which case we estimate a logit model. We report both probit and logit regression outputs.

Our primary interest is to evaluate partial (or marginal) effects for covariates. For a continuous regression, marginal effect is defined as

$$\frac{\partial Prob(X)}{\partial x_j} = \beta_j G'^{(X\beta)}, \quad (9)$$

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

In Table 10 report regression results from two specifications, estimated by probit and logit. The first specification is estimated for LFS and CBRD datasets, in models (1) – (4). The second specification, incorporating information from and excluding provinces, is estimated for CBRD data. We exclude provinces as they do not provide substantial explanatory power and largely deprive the degree of freedom.

Our finding from gender analysis in Section 5.4 is confirmed - probability of being deprived in labor market outcomes is significantly higher for female respondents in 2020. Deprivation gap between women and men amounts to 11 – 12 percent, which is significant at the one percent level. No substantial gender gap is observed in 2018.

Married individuals are systematically less deprived in 2018, while the difference vanishes in 2020. In 2018, married individuals are less likely to be deprived from labor market outcomes by 7.6 percent, significant at the 1 percent. Pandemic eliminated the difference among married and non-married, suggesting that that married individuals have been affected disproportionally.

The likelihood of deprivation in rural areas, relative to that in capital, is higher by 11-12 percent in 2018. In 2020, the difference is not significant. However, when dropping provinces, excessive deprivation in rural areas in 2020 is observed, amounted to 12 percent.[4] When adding types of training, the effect of rural areas increases by around 4 percent (models (5) and (6)). Overall, we conclude that, in regular times, deprivation in rural areas are systematically high, which is consistent with our early finding regarding the agricultural and related sectors. During pandemic, deprivation from labor market outcomes becomes more widespread and uniform, and the rural dimension becomes less distinguished in terms of excessive deprivation.

Regional differences in deprivation is not highly distinguished. We observe excessive deprivation only in Aragatsotn, relative to the reference region, which is Vayots Dzor. Our conclusion is that, while controlling for rural-urban differences, there is no substantial variation of multi-dimensional deprivation from labor market outcomes explained merely by regional differences. This result does not contradict with our earlier results from regional analysis in Section 5.3, since regression analysis enables to retrieve partial correlations while in that section, we calculate deprivation indexes for each province separately.

Table 11. Regression results. Marginal effects are reported

	Probit		*Logit*		*Prboit*	*Logit*
	LFS	*CBRD*	*LFS*	*CBRD*	*CBRD*	
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Female	0.008	0.116***	0.009	0.117***	0.114***	0.115***
	(0.022)	(0.029)	(0.022)	(0.029)	(0.035)	(0.035)
Married	-0.076***	0.025	-0.076***	0.027	0.032	0.035
	(0.023)	(0.029)	(0.023)	(0.029)	(0.034)	(0.034)
Rural	0.155***	0.079	0.158***	0.083	0.164***	0.162***
	(0.059)	(0.134)	(0.060)	(0.131)	(0.052)	(0.052)
Non-capital urban	0.04	-0.062	0.047	-0.056	-0.01	-0.01
	(0.059)	(0.136)	(0.061)	(0.132)	(0.035)	(0.036)
Aragatsotn	0.206***	0.009	0.195***	0.004		
	(0.072)	(0.152)	(0.070)	(0.149)		
Ararat	0.115*	0.033	0.110*	0.028		
	(0.061)	(0.142)	(0.060)	(0.138)		
Armavir	0.054	0.018	0.053	0.012		

[4] We do not report this specification for LFS and CBRD datasets, but they are available upon request.

	(0.065)	(0.141)	(0.065)	(0.138)		
Gegharquniq	0.1	0.061	0.1	0.057		
	(0.066)	(0.143)	(0.065)	(0.140)		
Lory	0.059	0.076	0.06	0.071		
	(0.062)	(0.144)	(0.062)	(0.141)		
Kotayq	0.051	0.127	0.051	0.122		
	(0.062)	(0.138)	(0.062)	(0.135)		
Shirak	0.055	0.142	0.054	0.136		
	(0.065)	(0.145)	(0.064)	(0.141)		
Syuniq	-0.018	-0.107	-0.017	-0.122		
	(0.071)	(0.152)	(0.072)	(0.152)		
Tavush	0.089	-0.043	0.09	-0.05		
	(0.065)	(0.146)	-0.064	-0.144		
Finance and insurance					-0.091	-0.092
					(0.060)	(0.062)
Manufacturing					-0.056	-0.059
					(0.106)	(0.110)
Service					0.208***	0.206***
					(0.046)	(0.046)
Information & communication					0.141***	0.141***
					(0.048)	(0.047)
Education					-0.211***	-0.212**
					(0.081)	(0.086)
Public sector					-0.112	-0.115
					(0.109)	(0.116)
Management					-0.201**	-0.207**
					(0.087)	(0.095)
Observations	1,451	1,155	1,451	1,155	881	881
Pseudo R^2	0.0562	0.0277	0.0564	0.0278	0.0695	0.0693

Note. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Finally, among sectors in which individuals in 2020 took training, service, information & communication, education, management are significant, relative to training type categorized as “others”. Individuals taking trainings in service and information & communication are on average more deprived by 21 percent and 14 percent, respectively. These are individuals who want to change their status in labor markets, from “non-deprived” to deprived. Individuals, taking training in the area of education and management, are less deprived by around 21 percent. They are more likely to make efforts to improve their skills and knowledge and get a better status in labor markets.

Chapter 7: Conclusion

From our study, we reach to a number of conclusive remarks. We observe systematic positive differences between deprivation scores constructed from CBRD and LFS datasets. Large differences are particularly observed for income, employment status, work time, working hours, work change, child & elderly care, reasons for quitting job and offer refused. From the close inspections of 3 multidimensional deprivation indexes, headcount ratio (H), adjusted headcount ratio (M0) and average and intensity of deprivation (A), we confirm that labor market conditions have been deteriorated in times of COVID-19, resulting in more difficulties in access to labor markets for Armenians.

From the contribution analysis we learn that education is the primary contributor to multidimensional deprivation from labor market outcomes in both 2018 and 2020. The 2020 dataset is by randomly more than doubling the number of individuals not deprived in education. Education, however, continued to be the number one contributor of adjusted headcount ratio. This is an important result from the policy perspective, since education is not considered as a main driving factor of multidimensional poverty in Armenia, when taking secondary education as a deprivation threshold (Grigoryan et al., 2021).[5] In our case, education with the threshold of secondary level continues to be a contributor of the adjusted headcount ratio in 2018, while it is not in 2020. Despite the deprived quality education since the break of the Soviet Union, it plays a rather central role in shaping an individual's status in labor markets.

In 2020, unemployment is the second contributor, while its contribution in 2018 is negligible. Profession mismatch is the second contributor in 2018. The change in the second highest contributor in 2020 indicates the difficulty, Armenians experience in finding a job during pandemic. Profession mismatch seems to be a secondary issue in 2020 in labor markets compared to finding a job.

Concerning rural-urban and regional differences, we conclude that in 2018 deprivation in rural areas are systematically high. During pandemic, deprivation from labor market outcomes becomes more widespread and uniform, and the rural dimension becomes less distinguished in terms of excessive deprivation. Regional differences are explained by rural and industry

[5] This is due to the heritage of an established and close-to-mandatory secondary educational system from the Soviet time makes it almost impossible that adult member has less than a secondary education.

concentration differences, otherwise they seem to have no substantial power to explain variation of multidimensional deprivation.

The gender dimension of our analysis shows that pandemic has resulted in gender gap in terms of the access to labor markets and the appropriation of labor market outcomes. Females are more deprived in terms of lower income and losing jobs.

From sectoral analysis, we identify the following patterns. Sectors, vulnerable from the labor market outcome perspectives, such as agriculture and construction, continue to be non-attractive to improve conditions through trainings. Sectors, such as information & communication and service, have the potential to help individuals to overcome unfavorable labor conditions. Finally, there are sectors, in which training can help further improve skills and knowledge and get better conditions labor markets.

In the end part of our research, we conduct regression analysis in order to retrieve net effects of individual, spatial and sectoral characteristics on a binary deprivation score. Most of the results obtained from previous sections are confirmed in the *partial effects* framework.

Chapter 8: Policy Briefs

8.1 Contributions Analysis

According to our research, education contributes to multidimensional deprivation from labor market outcomes most. The second highest contributor differs in 2018 and 2020. In 2018, profession match is the second highest contributor, little less than the contribution of education. In 2020, the second highest contributor is the employment status – unemployment contributed to M0 by 19 percent, while its contribution in 2018 was only 1.4 percent. Contribution of profession match in 2020 falls below its weight, suggesting that high deprivation observed in times of pandemic cannot be explained by skill mismatch in the labor market. Interestingly, neither job status nor no-job status does not have significant contribution to the adjusted headcount ratio, suggesting that indicators within these dimensions do not play a critical role in explaining deprivation from labor market outcomes.

The role of education is central in explaining deprivation from labor market outcomes both in regular and crisis times. Even current educational institutions, which lack in quality and do not satisfy up-to-date standards and expectations of advanced industries such as finance or information and communication, can help improve the access to labor markets for workforce. Strengthening existing incentives and introducing new incentives mechanism are vital for the young to get a higher education degree, given the efforts on quality improvement of education entities can be an efficient policy from the employment and other labor market outcomes perspectives.

Our analysis shows that even in crisis times, such as pandemic or the Nagorno-Karabakh war, higher education is key to sustain the status in labor market. Pandemic is a global shock affecting most of societal layers of population. Higher education, according to analysis, turns to be one of the buffers which helped Armenian citizens to preserve their labor market status and hence wellbeing. Investing in education is key to increase resilience of social wellbeing towards adverse shocks, may it be global or local.

Work Armenia Goal 1 is directly related to the human capital development in order to enhance the employability by matching the labor skills to the job market. Activities that are identified to be carry out under the Goal 1 are (i) institutional and content modernization, (ii) remote educational modules development for graduate programs, (iii) increase the competitiveness of graduates and enlarge their employability opportunities. Within these directions the Government seeks to closely cooperate with higher educational institutions as well as with employers to ensure that the academic-job market alignment is in place.

The current system of state funded scholarships should be revisited in order to create a more rewarding mechanism for students who demonstrate excellent academic performance. Also, the internship system in the universities needs to be revamped. The internship tasks should be well aligned with the academic program learning outcomes and those tasks should be relevant and provide an opportunity for students to enhance their critical and analytical thinking skills. The internship assessment mechanism should be rigorously structured so that this experience can better bridge the student to the employment.

Furthermore, one of the pillars of the Employment Strategy for 2019-2023 is developing more active policies targeted to youth employment increase, in particular those who just enter the job market. This strategy also underlines the importance of voluntary work experience as a stepping stone to the job market and skills acquisition. Concerning the profession match, it is important to align employment programs for youth, who enter labor markets first time and are more exposed to profession mismatch. Programs should be designed for young individuals in the age 16 – 29, particularly women in this age category who constrained more intensively due to maternity leave and gender gaps stemming from social norms and institutional developments.

8.2 Regional Analysis

The Government of Armenia program for 2019-2023 prioritizes the development of a number of economic sectors (such as agriculture, tourism) and their support mechanisms. The regional dimension of agriculture from the labor market perspective is highlighted in our study. Agriculture is dominant in provinces, featured by the proportion of respondents with particularly high deprivation in profession match and education. Also, labor market infrastructures are least developed in rural areas, which increases the likelihood of (multidimensional) deprivation from labor markets outcomes.

Work Armenia Goal 3 focuses on labor market coverage enlargement. In particular, one of the objectives is to promote employment in all administrative districts of Armenia. Our findings support this goal. Regional differences are not extreme, while the overall excessive deprivation is observed in 2020, compared to 2018. That is, employment promotion efforts should be invested throughout the country, in all regions.

This, however, does not mean that there are no significant regional differences. For example, unemployment in Shirak is traditionally high, and COVID-19 made employment conditions even worse. The second highest unemployment rate is observed in Kotayq, which has a high share of manufacturing in the industry structure. Regional differences, therefore, are not only due to rural-urban differences, but inherent to industry structure (the case of Kotayq province) or explained by early developments (in the case of Shirak marz).

So far, to a certain extent, the government employment programs in regions remain under-developed because oftentimes those programs do not take into consideration regional peculiarities and specific challenges. Generally, the Armenian Government recognizes that there is a need to develop employment and economic development programs at the regional level in order to reflect on each region's socioeconomic situation and development potential.

The Employment Strategy for 2019-2023 lays down the importance of elaborating and implementing employment programs that take into consideration regional specificities by classifying them as follows:

- Social-economic specificities of the region,

- Unemployment level of the region,
- Habits and social-psychological characteristics of the local population in the region.

While our study does not shed light on habit and social-psychological characteristics, we provide a number of important insights to understand the specifics of socio-economic developments through the lenses of labor market outcomes. Rural-urban differences, disproportional regional development and the COVID-19 impact (the latter increasing existing gaps in regional dimensions) suggest that the government strategies and derived policies need to be region specific, with strong focus on highlighted dimensions from the labor market perspectives, which are education, unemployment and profession match. These dimensions are consistently dominant in all provinces and the capital, in the structure of multidimensional deprivation indexes. Interestingly, remote provinces do not pattern excessive deprivation, indicating that multidimensional deprivation from labor market outcomes, largely explained by the above 3 dimensions, is widespread in the country. Contribution of education to multidimensional deprivation from labor market outcomes is excessive even in Yerevan in both 2018 and 2020, despite the high concentration of higher education entities in the capital.

8.3 Gender Analysis

Work Armenia Goal 3 focuses on the labor market coverage enlargement, whereby one of the set priorities is to develop and implement programs in order to boost female labor force integration into the job market. According to the National Statistical Service of the Republic of Armenia, in 2020 women constitute 55 percent of the Armenian labor force. Nevertheless, only 47 percent is active in labor markets. The Employment Strategy for 2019 -2022, on the other hand, emphasizes the importance of fair treatment towards and working hour conditions for women. Overall, the Strategy stresses the need to for creating equal opportunities for females and males.

Is low labor force participation among women explained by labor market conditions or it is explained by social norms and institutional development factors (beyond labor market conditions)? Also, does gender gap in labor market outcomes, if any, increase in critical times or both men and women suffer equally? Our study addresses these questions and provides important insights for drawing new and updating existing policies.

Based on the 2018 LFS data, our study shows that there is no systematic gender gap in deprivation from labor market outcomes. Even the difference in headcount ratios for the lowest cut-off is negative, indicating that women are less deprived from labor market outcomes than men. The sign changes for higher cut-offs, but the difference is not significant. Contributions from indicators from "job" or "no-job" status are not particularly high for women, suggesting that more specific institutional settings such as contractual relationship or childcare are not obstacles for women to be active in labor markets. These results do not change when taking all observations from LFS into the model. We conclude that in regular times, deprivation from job market participations for women are driven by the same factors (education and profession match) as for men. Gender gap in labor market outcomes should be searched in social norms and institutional developments which are not captured by our indicators and dimensions.

Gender gap, however, emerges in times of COVID-19. Pandemic has resulted in gender gap in access to labor market and the appropriation of labor market outcomes. Females are more systematically deprived from labor outcomes, in terms of lower income (31 percent of deprived cases for female and 13.59 percent of deprived cases for males) losing jobs (29 percent for females versus 26 percent for males). Women turn to be sensitive to negative changes in labor market conditions, and primarily to work income and employment status. This finding suggests that government policies, aimed at decreasing gender gap 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, such as distance work and flexible working time schedule, as well as provision of more attractive employment package covering insurance, child care and maternity leave. While in normal times such polices may not be of primary importance to make working conditions particularly attractive for women, they can be instrumental to prevent the emergence of gender gap in labor markets in hard times such as pandemic.

8.4 Sectoral Analysis

Employment Strategy 2019- 2022, adopted by the Government of Armenia, refers to sectoral dimension of (un)employment in the context of disproportional regional development. Employment programs in targeted industries such as agriculture or tourism are considered as policies to mitigate differences in regional developments. Our research in the area of employment polices specific to sectors shows that the Armenian Government needs to make systematic efforts to develop sector-specific employment policies, disentangled from proportional regional development policies. Interaction between sectoral and regional dimensions, translated into labor market outcomes, is not straightforward and rather complex. Proportional regional growth does not assume homogenous industry structure among regions. Cluster theory highlights the emergence of regional clusters, critical for sustainable development of an economy. Neighboring region(s) may belong to one geographic cluster of a specific industry or different parts of a region may belong to different clusters. That is, regional and cluster areas may be very different. Also, sectoral policies are mostly built on the notion of efficiency, which is unequally increasing. On the contrary, mitigating existing income and wealth inequalities should be at the heart of the proportional regional development policies. In what follows, state policies aimed at reaching proportional regional growth need to be identical with polices addressing sectoral development of a country.

From the sectoral analysis, we conclude that, in regular times, labor force engaged in agricultural and related sectoral activities are exposed to multidimensional deprivation from labor market outcomes most. Education and profession (skill) mismatch are the dimensions, whose contributions to adjusted headcount ratio are the highest. Those respondents, who took training in the area of agriculture are deprived from labor market outcomes most. However, there are only few individuals who took trainings in the area of agriculture.

The second most vulnerable sector in 2018 was construction. This sector did not fully recover after the global crisis 2008 – 2014. In the 2020 data, there are only individuals who took training(s) in the area of construction, suggesting that trainings may not be efficient to improve skills in construction.

Overall, we identify 3 patterns from the sectoral analysis. Sectors which are vulnerable from the labor market outcome perspectives, such as agriculture and construction, continue to be non-attractive for individuals and/or training organization to improve conditions through trainings. There are sectors, such as information & communication and services, which can "rescue" individuals from current unfavorable labor related conditions. These sectors enable labor force, previously not successful in the market, to catch-up making systematic learning efforts. These are information & communication and services. Finally, there are a number of sectors (such as finance and insurance and education) in which training can help further improve skills and knowledge and acquire better conditions labor markets.

Our policy recommendation is to provide fundamental educational opportunities to address sectoral dimension of deprivation (from labor market outcomes). While trainings can be beneficial for individuals specialized for the third category sectors, they cannot be useful for individuals changing their specialization area, say, from construction to IT. Real opportunities need to be offered for occupational shifts such as specialized master programs with affordable tuition fees. In Armenia, labor demand by the private sector is not met in a number of specializations, and sectoral development from the labor market perspective should be viewed with strong linkages to quality education.

Appendix

Table A1. Descriptive statistics from CBRD 2020 Survey

Variables (deprived if 1)	Obs.	Mean	St. dev.	Not deprived=0	Deprived=1
Income	1,451	0.1992	0.3995	0	1
Education	1,451	0.3398	0.4738	0	1
Employment status	1,451	0.2509	0.4337	0	1
Employment benefits	1,451	0.3556	0.4789	0	1
Contract	1,451	0.0627	0.2425	0	1
Contract duration	1,451	0.0724	0.2592	0	1
Work time	1,451	0.1420	0.3491	0	1
Working hours	1,451	0.1571	0.3641	0	1
Union	1,451	0.5403	0.4985	0	1
Work change	1,451	0.5093	0.5001	0	1
Child/elderly care	1,451	0.1571	0.3641	0	1
Profession match	1,451	0.1964	0.3974	0	1
Reasons for work termination	1,451	0.3060	0.4610	0	1
Work search	1,451	0.0848	0.2786	0	1
Offer refused	1,451	0.4163	0.4931	0	1
Female	1,164	0.5515	0.4975	0	1
Married	1,451	0.4728	0.4994	0	1
Rural	1,451	0.1206	0.3258	0	1
Capital	1,451	0.3122	0.4636	0	1
Non-capital urban	1,451	0.5672	0.4956	0	1
Yerevan	1,164	0.4158	0.4931	0	1
Aragatsotn	1,164	0.0335	0.1800	0	1
Ararat	1,164	0.0679	0.2516	0	1
Armavir	1,164	0.0739	0.2617	0	1
Gegharquniq	1,164	0.0601	0.2378	0	1
Kotayq	1,164	0.1194	0.3244	0	1
Lori	1,164	0.0653	0.2471	0	1
Shirak	1,164	0.0533	0.2247	0	1
Syunik	1,164	0.0455	0.2086	0	1
Tavush	1,164	0.0550	0.2280	0	1
Vayots Dzor	1,164	0.0103	0.1011	0	1

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