JOBS WORKING PAPER
Issue No. 65

Understanding and Predicting Job Losses Due to COVID-19: Empirical Evidence from Middle Income Countries

Maho Hatayama
Yiruo Li
Theresa Osborne

WORLD BANK GROUP
Jobs

UNDERSTANDING AND PREDICTING JOB LOSSES DUE TO COVID-19: EMPIRICAL EVIDENCE FROM MIDDLE INCOME COUNTRIES

Maho Hatayama

Yiruo Li

Theresa Osborne

WORLD BANK GROUP
Jobs

Acknowledgements

This work was prepared under the World Bank's JobsWatch COVID-19 project (P174663). The production and publication of this report has been made possible through financial support from the World Bank's Jobs Umbrella Multi-donor Trust Fund (MDTF), which is supported by the UK's Foreign, Commonwealth & Development Office/UK AID, the Governments of Austria, Germany, Italy, Norway, the Austrian Development Agency, and the Swedish International Development Cooperation Agency.

We with to thank Michael Weber, David Newhouse, Ruth Hill, and Sebastian-A Molineus for helpful suggestions and Ian Walker for his support. Special appreciation goes to Alan Fuchs and Cristobal Ridao-Cano for their incisive and constructive comments.

Understanding and Predicting Job Losses due to COVID-19: Empirical Evidence from Middle Income Countries

December, 2021

Maho Hatayama, Yiruo Li, Theresa Osborne

World Bank Jobs Group

Abstract

This paper utilizes firm survey data to understand which formal private sector jobs are most at risk from COVID-19 or similar future crises, based on empirical evidence from two middle income economies. In particular, it estimates the importance for formal private-sector job losses of various COVID-19 pandemic-related labor market shocks and mitigating factors, such as the closure of non-essential industries, workers' ability to perform their jobs from home, infection risks to workers, customers' infection risk, global demand shocks, input supply constraints, employers' financial constraints, and government support, in determining the level and distribution of job losses. This provides an empirical identification of the main risk factors for job loss and a basis for predicting the level and distribution of these losses due to the crisis. The methodology is applied to permanent formal private sector (PFPS) jobs in core productive manufacturing and services sectors (captured by World bank Enterprise Surveys) in Jordan and Georgia, which contain the requisite data to link occupational structure, task content, and firm-level shocks. Comparing empirical findings across the two, the paper assesses the degree of commonality of these risk factors. Job losses are projected for different groups within the employed population prior to the outbreak of COVID-19 and compared with post-crisis labor force data. The results indicate that in these countries the level of job losses is predominantly due to a reduction in demand rather than a reduction in the supply of labor. Closures, global demand shocks, supply disruptions, and other unexplained demand side shocks are significant determinants of jobs lost. Sensitivity of employment to closures, supply disruptions, and sales shocks was of similar magnitude in both countries; however, variation in infection risk was a significant determinant of sales only in Georgia. At the same time, Georgian formal firms were better able to rebound their sales and hire back workers than formal firms in Jordan. Finally, the paper finds no evidence that firms with workers performing tasks that can be performed from home were better able to preserve jobs, given the dominant role of firm-level demand and supply chain shocks.

Keywords: COVID-19, firms, job loss, labor market impacts

JEL Codes: E24, J15, J16, J21

Table of Contents

FIGURES

1. Introduction

It has been clear from the start of the COVID-19 pandemic that it would adversely impact workers worldwide. Potentially massive job losses were foreseen as resulting from closures and other public health measures, and governments responded with policies to mitigate income and job losses and shore up welfare. However, given the interplay of shocks to labor demand and supply as the crisis unfolded, targeting and calibrating benefits to those impacted or to preserve jobs that would be viable after the crisis has proven challenging (Fujita & Moscarini, 2017). The limited availability of data on jobs outcomes, especially in many low- and middle-income countries, has only added to the difficulty of designing cost-effective mitigation measures.

A spate of papers appeared early in the pandemic characterizing the likely risk factors for job loss (Mongey et al., 2020; Avdiu and Gaurav, 2020). Without data to the contrary, risk indices were based on such factors as the ability to work from home or exceptions to lockdowns for essential activities, which appeared particularly germane to the early phase of the crisis and, arguably, to developed economies. Once data became available, a literature emerged documenting the scale and distribution of realized job losses, including by gender, educational attainment, sector of employment, and income level, especially in developed countries but not excluding developing ones (Palacios-Lopez et al., 2021, Kugler et al, 2021). Some papers emphasized the supply side (e.g., Dingel and Neiman, 2020), and others considered infection-risk-induced demand shocks in rich countries (e.g., Aum et al., 2020). Later in the crisis, data and stylized facts began to accrue on how firms in developing countries have been impacted, how they have adjusted to the crisis, how impactful policy responses have been, how their workers have been affected (Apedo-Amah et al, 2021). Yet empirical evidence on the importance of various channels of impact on job loss in developing economies, and therefore the risk of further job losses, has remained little understood.

This paper's main contributions to the literature on COVID-19 labor market impacts are twofold. First, it adds to the evidence base on the factors most important to (formal, private sector) jobs losses as well as on how well these factors alone can explain the demographic patterns of job losses observed. Second, it provides a general methodological approach for predicting such impacts in other near-term periods and similar country contexts. To develop the evidence base, we utilize firm, labor force, and other data to identify the main determinants of job loss due to the pandemic. This includes an estimation of the empirical importance of the ability to work from home, infection risk, digital technologies, and other factors featured in the early literature, as well as a variety of key demand-side factors. This empirical estimation comprises the first major step of our methodology. In our second step, we use the empirical model from the first step to project job losses onto the pre-COVID labor force by sector, firm-size, and broad occupational category. This allows us to tally projected loss rates in the aggregate, as well as by demographic group. To further test our methodology and provide evidence on the extent to which economywide, sector, and firm-level drivers of job loss can explain the ultimate demographic trends in the data, we compare these predictions to data from a pandemic-period labor force survey.

Finally, to enhance our methodological contribution, we provide a comparative perspective of the evidence from two upper middle income economies — Jordan and Georgia, where the requisite data were available to link demand side shocks to workers' attributes and occupational task content. Our country choices are also especially relevant, given that by some metrics, middle income country labor markets have been the most heavily hit by COVID-19. [1] The two-country comparison permits us to explore the possible

[1]World Bank high frequency phone surveys (HFPS) show that the percentage of people working before covid (over 18) no longer working at the time of the survey is higher for MIC's (at 36 for UMICs, 32 percent

generalizability of our evidence for quantifying likely job losses in other countries. We then suggest approaches for utilizing the results to predict job losses elsewhere.

Data limitations in developing countries make it impossible to provide a full accounting of risks to all jobs, even for these two economies selected in part for their relatively comprehensive data availability. Because relevant data on all employment types is lacking, we can only analyze the drivers of risk to permanent formal private sector (PFPS) jobs. These are jobs held full time and for longer than a year at a formal private company, as defined in the World Bank's Enterprise Surveys (WBES). Informal work is a mainstay in middle income countries, can be a shock absorber when the formal sector experiences a downturn, and can also be impacted through demand side channels by the formal labor market. However, we cannot analyze the informal employers' decision as we can for formal firms due to the lack of similar data. Moreover, PFPS jobs still represent an important share of all jobs in such countries and a much higher share than in low-income countries. [2] Jobs with formal firms are crucial to development as these jobs tend to be more productive, remunerative, and desirable, but are scarce relative to labor supply. [3] Informal workers and the self-employed likely share major risk factors with formal firms, but our findings are not necessarily generalizable to them.

---

for LMICs) than for LICs (at 25 percent), using a simple average across countries surveyed. Similarly, according to ILO (2021), using nowcasting methods "During 2020, lower-middle-income countries experienced the greatest losses in working hours, which stood at 11.3 per cent, well above the global average of 8.8 per cent." However, a higher share of households in low- and lower-middle income countries experienced some income loss than in upper-middle and high-income countries (World Bank HFPS).

[2] Given differential labor market frictions in the formal versus informal sectors, PFPS job losses may understate job losses in the informal private sector early in the crisis but could overstate them later on or as economies improve. As in Alfaro et al. (2020), changes in employment are more rapid for informal firms and workers than for permanent formal sector employment, and these workers may have different profiles.

[3] Although non-permanent workers for such firms could be more rapidly affected by the crisis, they represent a very small share of formal firm employees: 5-10 percent in Jordan (MENA Monitor Survey, 2021), and 3 percent in Georgia (LFS, 2019).

Our main findings are as follows. First, shocks to labor demand predominated over supply side shocks to formal private sector jobs in both countries. These were primarily driven by disrupted input supply, COVID-related temporary closures, and other shocks to sales. For each week of closures due to the pandemic, approximately 1.2 percent of PFPS jobs were lost, and the overall responsiveness of jobs to changes in sales was very similar in the two countries – for each 1 percentage point of lost sales, there was an average 0.4 percent adjustment in PFPS workers in both countries. The occurrence of disruptions to the supply of inputs also had large and significant implications for sales and labor demand in both countries. In addition, infection risks to customers accounted for a large share of sales declines and therefore job losses, but only, according to our evidence, in Georgia.

Other determinants of labor demand had a much smaller impact. The ability to introduce digital solutions and support to firms had apparently little effect: Although the receipt of wage subsidies (firm reported) mitigated job losses in Jordan, they had small effects relative to the other significant factors, and there was no evidence that other firm support measures saved jobs in the timeframes considered. In Georgia, similarly, we found no evidence that any policy support measures induced firms to retain more workers. [4] Although these measures could have protected jobs to some extent, by supporting aggregate demand, limiting scarring effects and thereby setting the stage for the recovery and subsequent job growth, we were not able to confirm such impacts in the time frame studied at the firm level. At the same time, the binary (0-1) variables capturing policy support and sample may not provide sufficient power to capture these effects. If policies did fail to affect job losses, this could be because their targeting or reach was inadequate. Stylized facts reported by Cirera et al. (2021) suggest that policy support measures in developing countries have suffered from limited reach, mismatch between policies

[4] Although financial difficulties were correlated with permanent closures, there was no clear way to address possible simultaneity between these two outcomes.

provided and those most sought, and mis-targeting of support. Finally, we found no evidence that firms with a higher share of employees working from home were able to retain more permanent workers. Although a number of firms adopted or expanded their use of digital / online tools, we found no evidence that these business adaptations saved significant numbers of PFPS jobs. Our results suggest that although investments in digital technology can be instrumental for certain sectors, firms, occupations, and firm functions, they cannot fully substitute for face-to-face interaction or physical presence in all sectors, and they may not compensate adequately for a lack of demand.

The methodology produces a distribution of job losses by demographic group that is similar across the two countries. For both, the methodology predicts a greater percentage of lost jobs for men; for those under 25 (and in the case of Georgia, over 45); for those with less education and with lower pre-COVID wage levels.

These predictions are not always borne out in the observed data, however. Overall, we find that the model predicts the level of further job losses fairly well. It predicts the distributional impacts by gender, nationality, and educational attainment , but it fails to predict the observed differences by age group and wage level. This is likely in part due to the lack of more detailed and specific data at the firm level on employment and employment losses by occupation. Results also align with observed high frequency phone data from Georgia by age group and educational attainment, but the phone survey is not sufficiently comparable to reach conclusions on the methodology's accuracy for that country. In addition, sector- level predictions are difficult to verify given definitional mismatches in the data, but the rates of job loss generally rank similarly to those observed. Overall, because our projections rely only on sector-, firm-, and broad occupational- class level shocks, we attribute the divergence between observed and projected outcomes at least in part to unobservable behavioral differences on the part of employers and workers that are correlated with gender, age, and unobserved skills or productivity, in addition to firm data limitations.

The rest of the paper is organized as follows. The next section summarizes the relevant literature on the jobs impacts of COVID-19. Section 3 presents the context in Jordan and Georgia, describes the data we use, and presents our methodology. Section 4 presents our econometric results for both countries. Section 5 presents the methodology for projecting job losses onto the labor force; projection results, and a comparison of projected future job losses with survey-measured future ones. Section 6 presents PFPS job losses in the context of what we know about job losses in other segments of the labor market. Section 7 discusses applications of our method to other contexts and the possible generalizability of our findings. Section 8 concludes with a discussion of the methodology, policy implications and directions for future research.

2. Related Literature

Our work contributes to the rapidly expanding literature aiming to understand the impacts of COVID-19 on labor markets. Early in the crisis, most of the empirical studies focused on high-income countries given that real time data is more available for them. For example, studies from Australia (Guven, et al., 2020), Austria (Baumieh & Ziegler, 2020), Italy (Casarico & Lattanzio, 2020), the European Union (Pouliakas & Branka, 2020), Germany (Alipour et al., 2020), Greece (Betcherman et al., 2020), South Korea (Aum et al. 2020), Sweden (Hensvik et al., 2020; Juranek et al. 2020), the UK (Crossley et al., 2021), and the U.S (Adams-Prassl et al., 2020) all aimed to quantify the crisis' overall impacts on employment or working hours and, where feasible, to identify the groups of workers most affected.

Many studies highlighted the heterogeneous effects of the pandemic on different segments of workers and traced these in part to the differential ability to work remotely (Adams-Prassl et al., 2020), but also to issues such as infection risk, labor market attachment or tenure, and policy support measures (Lee et al., 2021; Chetty et al., 2020; Montenovo et al., 2020; Dang, Huynh & Nguyen, 2020). Prassl et al. (2020), for example, find that job losses differed substantially even across rich countries . They were much lower in the initial phase of the crisis in Germany, at 5 percent, than in the U.S. (18 %) and the U.K (15 %). They also find that the pandemic has exacerbated existing inequalities across workers within countries. Chetty et al. (2020) use real-time data from private companies for the United States and show that low-wage workers are more likely to experience job losses that lasted several months compared to high-wage workers. Lee et al. (2021) also find that the negative impact on employment was larger for women, minorities, the less educated, and young people in the United States, and Albanesi & Kim (2021) find similar gendered effects on the US labor market. In addition, del Rio-Chanona, et al. (2020) estimate supply and demand shocks in the U.S. in the earlier stage of the pandemic using pre- and post-COVID datasets. In Australia, the impact on unemployment and reduced working hours was in the low single digits. However, workers with up to high-school education experienced larger reductions in their labor force participation and working hours than others. Moreover, immigrants and individuals with shorter job tenure or occupations unsuitable for remote work were hit the hardest in terms of unemployment (Guvet et al., 2020). Garrote Sanchez et al. (2020) use information on essential sectors in Italy and the U.S. and the recent 2018 European Labour Force Survey (EU LFS) to identify workers in non-essential industries. They find that jobs most at risk account for 30 percent of all EU employment, and a larger share of jobs in economically disadvantaged regions tend to be vulnerable ones.

After lockdown orders had eased, some studies consider the potential shocks to labor supply arising from workers' reluctance to work due to infection risk on the job. For example, Aum et al. (2020) show that fear of infection contributed to reductions in employment in the Republic of Korea, where the government used intensive testing and contact tracing rather than enforcement of lockdown measures. They find that workers in high-contact industries can be affected the hardest and experienced the greatest reductions in local employment.

Empirical studies on developing countries were much fewer given the data limitations. Some authors focused on anticipating both the magnitude of impacts and how they would likely be distributed by taking lessons from the developed world. Some posited that certain job characteristics raised the risk of job loss. For example, Zheng et al. (2020) and Adams-Prassl et al. (2020) estimated the degree to which people can work from home during the pandemic to mitigate workplace closures or capacity limits. Other studies relied on occupation-level data from O*NET (Dingel & Neiman, 2020; Avdiu & Nayyar, 2020) or workers' task content information from pre-COVID labor force and skills surveys (Hatayama et al., 2020; Gottlieb et al., 2020; Delaporte & Pena, 2020) to assess the ability to working from home. For example, Hatayama et al. (2020) utilize data from 53 countries on the task content of jobs to assess the amenability to working from home and find that lower income countries and male, less educated and self-employed workers have jobs less amenable to working from home. Other studies considering the issue of remote work and closures predicted a job crisis disproportionately affecting lower income and female workers, who tended to hold more jobs requiring face-to-face interactions (Avdiu & Nayyar, 2020). The IMF (2020) also found that the high proportion of jobs involving personal contact and low amenability to working from home in Latin America made that region's jobs particularly vulnerable to loss relative to sales losses – largely due to exits from the labor force.

Some recent studies have also quantified adverse impacts on employment in developing countries, such as India (Beyer, Bedoya & Galdo, 2020; Deshpande, 2020; Dhingra & Machin, 2020) and Nigeria (Avenyo & Ndubuisi, 2020). Other studies such as Khamis et al. (2021) and Kugler et al. (2021) have conducted cross country analysis using data from high-frequency phone surveys (HFPS) conducted by the World Bank, covering countries across all developing regions. The former estimates that 19 percent of workers in low-income countries, 37 percent in lower-middle-income countries, 41 percent in upper-middle-income countries, and 26 percent in high-income countries experienced a work stoppage. Kugler et al. find that Larger shares of female, young, less educated, and urban workers stopped working than others. Gender gaps in work stoppage were particularly pronounced and stemmed mainly from differences within sectors rather than differential employment patterns across sectors.

As the crisis continues to unfold, more papers have turned to the importance of labor demand shocks. Using real-time surveys, a number of researchers have documented the impact on layoffs by private firms of sales loss, closures, or liquidity issues (Bachas, et al., 2020; Bartik et al., 2020; Adams-Prassl et al., 2020; Fairlie, 2020). Apedo-Amah et al. (2020) use a dataset measuring the impact of the COVID-19 pandemic on the private sector, which covers more than 100,000 businesses across 51 countries. They find that firms who have experienced a larger reduction in sales experienced a larger reduction in employment. Using real-time data on vacancy postings on online job portals in Sweden, Hensvik et al. (2020) find that postings fell by 40 percent even during the earlier period of the pandemic. It has also been clear that, due to either social distancing measures or consumer risk aversion, contact-intensive sectors, such as travel, restaurant, and other services, have been greatly affected (Mongey et al., 2020). The large job losses in other sectors, such as manufacturing, have not been as obvious to all *a priori*, whereas in other sectors, such as construction and agriculture, they may have been over-predicted due to the focus on the ability to work from home.

As the literature details, firms have been affected through multiple channels. First, the crisis affects levels and patterns of consumer spending. Domestic consumers reduce their mobility to reduce the risk of infection and avoid products and services that involve interactions with others (Andersen et al., 2020; Balleer et al., 2020). For example, Abay, Tafere and Woldemichael (2020) estimate how much the crisis affected demand for selected services across 182 countries using real-time Google search data. They find that the crisis led to a 63 percent reduction in demand for hotels and a comparable rate of increase in demand for ICT services. Firms have responded to reduced cash flow and high uncertainty by adjusting their investment (Boone, 2020) as well as their production and delivery technologies. Due to the disruption of supply chains, inventories have also been run down (Boone, 2020; Guan et al., 2020; Bonadio et al., 2020; Inoue & Todo, 2020). Trade has also been affected, possibly permanently (Baldwin & Weder di Mauro, 2020). Given these shocks, the ability to maintain workers depends on firms' ability to sustain their liquidity and solvency. Using World Bank Enterprise Survey data, Bosio et al. (2020) find that firms have suffered liquidity shortages regardless of their age, size and productivity levels. Alfaro et al. (2020) model the impact of the direct supply shock caused by lockdowns as well as demand shocks though consumer demand, supply chain disruption, and the overall aggregate demand effects on the Colombian labor market. They predicted that the crisis would result in 24 percent of jobs being lost and total wage income losses of 17 percent. They showed that 56 percent of jobs are at risk, with 67 percent at risk as the crisis deepens due to cumulative liquidity effects on firms (with losses relative to the 2019 baseline.) A forthcoming paper (Buba et al., 2021) analyzes cross country differences in jobs outcomes at formal firms using firm survey data and establishes that at least in the short term, countries with more highly regulated labor markets retained more formal jobs; that countries with more stringent lockdowns had greater job losses, and that on average countries with supportive policies have been more able to preserve these jobs.

Despite this rich literature on the labor market impacts of the pandemic, there have been limited studies that seek to empirically identify the factors that matter most in determining the level and distribution of jobs lost. This paper contributes to filling this gap.

3. Context, Data and Methodology

3.1 Data

We use linked firm-level and labor force survey data to empirically analyze job loss in formal private firms for both Jordan and Georgia. Firm data are provided by the COVID-19 Follow Up World Bank Enterprise Surveys (CFUWBES) for these two countries. These are surveys of companies included in a recently completed pre-COVID World Bank Enterprise Surveys (WBES) to measure the impact of the COVID-19 pandemic on the private sector. We analyze only the loss of a "permanent" job, because a firm's workforce level is the only job-related outcome that is effectively captured in the CFUWBES, and a job loss represents a more costly outcome for workers than other effects, such as reduced hours, wages, or temporary furloughs. In addition to firms' permanent workforce adjustments, the CFUWBES questionnaire includes variables capturing the operations of the business, sales, liquidity and insolvency, firms' technological adaptations, their expectations and uncertainty about the future, and public support received during the crisis. The WBES sampling approach is from the population of all registered establishments with five or more employees in manufacturing, retail, and other services sectors, designed to represent core productive sectors typically owned and operated privately. It does not include financial services, real estate and rental activities, or public service providers. Therefore, while it represents a major portion of the formal private sector, it does not capture all formal private sector employers. For Jordan, the baseline ES contains a total of 601 firms conducted from December 2018 to November 2019. The CFUWBES wave 1 (henceforth CFUWBES1) was conducted from July to August 2020, and the CFUWBES wave 2 (CFUWBES2) data was collected from November 2020 to January 2021. Both rounds of CFUWBES use the same sample as the most recent WBES to construct a panel. For Georgia, the baseline WBES contains a total of 701 firms interviewed between March 2019 and January 2020. The same firms were re-contacted in June 2020 for Wave 1 and in October/November 2020 for Wave 2.

In addition, we use recent labor force surveys to link firm data and predict potential effects on workers. For Jordan, we use the Jordan Labor Market Panel Survey (LMPS) 2016, which collects labor market information as well as data about specific tasks carried out at work. For Georgia, we use the 2019 Labor Force Survey (LFS) by the National Statistics Office of Georgia (Geostat). The LFS also provides information on employment for different socio-demographic groups defined by gender, age, education level, sector, occupations and earnings. Our final sample for all data sets includes "employed" individuals in the private sector.[5] In addition, we use the STEP (Skills Towards Employability and Productivity) survey for Georgia to understand workers' amenability to working from home.

To construct variables as proxies for labor demand and supply shocks, our paper also draws from three additional sources of data. First, we use the list of essential industries developed by the Italian government in the absence of published country-specific lists. As Italy was one of the countries affected earliest, the government had made a significant effort to determine essential industries. Their list uses NACE industrial classification codes, which can be mapped to the ISIC industry classification used in the WBES. We also use occupation-level data from the Occupational Information Network (O*NET) to estimate the infection risks of workers. O*NET has information on work activities data for 775 occupations on the level of 4-digit NAICS (North American Industry Classification System). We follow WEF[6] and calculate scores on the extent to which workers in given occupation face infection risks based on their responses to three questions regarding exposure to disease and infection, contact with others and physical proximity to others (details in

---

[5] We used LFS 2019 since the dataset covers a full year of repeated cross-sectional data and has sufficient observations to study PFPS workers. We are also cautious about using data on 2020 for our prediction, as the impacts of COVID-19 has already reflected in the dataset. Given one purpose of our paper is to develop a method predicting jobs lost in absence of post-COVID household level data, using the 2020 dataset from Georgia would undermine this objective.

[6] https://www.weforum.org/agenda/2020/04/occupations-highest-covid19-risk/. The three factors are equally weighted.

Appendix 1). Finally, we proxy changes in global demand by sector using the data from UN Comtrade and FlightRadar24. Appendix 1 contains more details on the construction of the variables used.

To complement our findings and assess the crisis impact on workers who are outside our model (i.e., not formally employed in the private sector), we utilize real-time surveys on labor markets. For Jordan, the Economic Research Forum (ERF) conducted the COVID-19 MENA Monitor Household Survey (CMMHH), a nationally representative panel survey conducted among mobile phone users aged 18-64. The baseline wave of this dataset was collected in February 2021. This is a reliable and detailed survey that is more similar in scope and design to the LFS than other surveys conducted during the pandemic, such as the World Bank's high frequency phone survey. For Georgia, the World Bank conducted a COVID-19 (Georgia) High Frequency Phone Survey (GHFPS) that cover a national random sample of mobile phone users aged 18-64. Both surveys aim to collect data on the socioeconomic impacts of COVID-19 on households and individuals, including information on job and income loss.

3.2 Pre-COVID Country Context

Both Jordan and Georgia had experienced relatively stable growth over the years prior to 2020. Jordan's real GDP growth averaged 2.4 percent between 2012 and 2020 and GDP per capita reached USD 4,405.5 in 2019. Georgia averaged real GDP growth in the years 2012-2020 of 4.1 percent (source: IMF World Economic Outlook, October 2021), and GDP per capita reached USD 4,272 in 2019.[7]

[7] In PPP terms, Jordan's per capita GDP in 2019 was $10,497.00, substantially lower than Georgia's level of $15,623.00.

Both economies were somewhat integrated with the world economy prior to the pandemic, but Georgia mores so. In 2019, merchandise trade as a percent of GDP was over 61 percent for Jordan and 76 percent for Georgia and services trade comprised 28 percent and 40 percent of GDP, respectively (WDI, 2019). Georgia had also posted a higher level of exports as a share of GDP (54.8 percent) than Jordan at 36.3 (WDI, 2019) and had also seen faster growth in unit export values than Jordan (WDI). Within services, Jordan was much more reliant on the travel and tourism sector, which accounted for around 18 percent of GDP and of total employment in 2019 (World Bank, 2021) relative to 7.6 percent of GDP and 5 percent of total employment for Georgia in 2018 (World Bank, 2019).

Table 3-2: Labor Market Statistics, 2019

	Unemployment Rate	Labor Force Participation (percent age 15+)
Georgia	11.6	62.9
Jordan	16.8	39.2

Source: WDI. National Estimates

Table 3-1: Employment Structure, Jordan (2016) and Georgia (2019)

Mode of Employment	Share of employed (all ages) Jordan	Georgia
1. Farmer (owns a farm/self-employed)	0.4	35.5
2. Business owner/self-employed (but not a farmer)	14.4	
3. Unpaid family worker on a farm	1.2	22.7
4. Unpaid family worker (but not a farmer)	0.4	
5. Wage worker for Government / public enterprises	29.6	17.2
6. Wage Worker for the private sector	54.1	24.6
Formal and regular	22.1	-
Permanent [1/]	21.7	11.0
Formal irregular or temporary	0.7	0.5
Informal regular or permanent	23.2	11.0
Informal Irregular or temporary	8.1	2.1

Source: Jordan Labor Market Panel Survey (LMPS) 2016 and Georgia Labor Force Survey (GLFS) 2019.
Note: GLFS 2019 does not distinguish between owner-operation of or unpaid family work on an on-farm versus an off-farm business Since GLFS 2019 does not include questions on regular/irregular workers, only temporary/permanent classification is reported in the table. For Georgia, permanent workers are defined as those reporting that they are permanent workers. For Jordan, permanent workers are defined as individuals who either report they are permanent

The labor market context pre-COVID varied somewhat between Georgia and Jordan as well. They each approached the regulation of labor markets differently. Georgia's labor market regulation is considerably more flexible in terms of permitted hours of work and contractual arrangements. It has no minimum wage, whereas Jordan's minimum wage is approximately 50 percent of value added per worker (Employing Workers Database (EWD, 2020). Georgia's regulatory requirements are also more flexible with respect to dismissing workers. No third-party notification or approval is required; nor are there priority retraining or rehiring requirements for dismissed workers. Jordan, in contrast, is among the 32 countries with the most stringent regulation of worker dismissals (including prohibiting dismissals for any reason without third party approval), and fixed term contracts are prohibited for permanent tasks (EWD, 2020).

Labor market outcomes entering the crisis also diverged. Unemployment in Jordan was more than 5 percent points higher and labor force participation 23.7 percentage points lower than in Georgia (Table 3-1). Jordan's female participation rate (13.4 percent in 2019)[8] is among the lowest in the world and female unemployment — 19 percent at the end of Q4 2019 was also relatively high just before the COVID-19 pandemic. Georgia's female participation and unemployment rates, in contrast, were 54.5% and 10.2%, [9] respectively. Georgia's population aged 25 or over was more educated, with 59 percent having completed at least post-secondary (2017, WDI/UNESCO) as compared with Jordan's 27 percent (in 2010, WDI/UNESCO).

For those who were employed in Jordan pre-COVID, a greater share of jobs was in the public sector and in formal private sector jobs than in Georgia.[10] The share of jobs by type

---

[8] National estimate, 2019. ILO models predict 14.6 percent in 2019.
[9] National estimate, 2019.
[10] To delineate formal from informal employment in the respective labor force surveys, which are available in the original micro datasets from the respective countries. Appendix Table 2, explains how we define "permanency" in CFUWBES (Jordan and Georgia), LMPS (Jordan), LFS (Georgia), and CMMHHS (Jordan).

of employment from Jordan's most recent pre-COVID labor force survey (2016) is shown in Table 3-2. Fifty four percent of jobs were private sector wage jobs, and approximately half of these were formal and permanent, with the rest being either informal, temporary/irregular, or both. Almost 30 percent of jobs were for the government or public enterprises, and 16.4 percent were in self-employment or family workers (on farm or off).

In Georgia, in contrast, 35 percent of jobs in 2019 were in self-employment and 22.7 percent in unpaid family work. Wage jobs for the public sector and for the private sector both comprised lower shares of jobs (17.2 and 24.6 percent, respectively) than in Jordan. Wage work for the private sector in both countries was overwhelmingly regular or permanent, and temporary work represented a very small share of private sector jobs (Table 3-2).

Informal employment constituted an important component of jobs in both countries. Beyond self-employment and employment by the family, much which may be informal, informal wage employment represented 31.3 percent of jobs in Jordan and 13.1 percent of them in Georgia (Table 3-2).

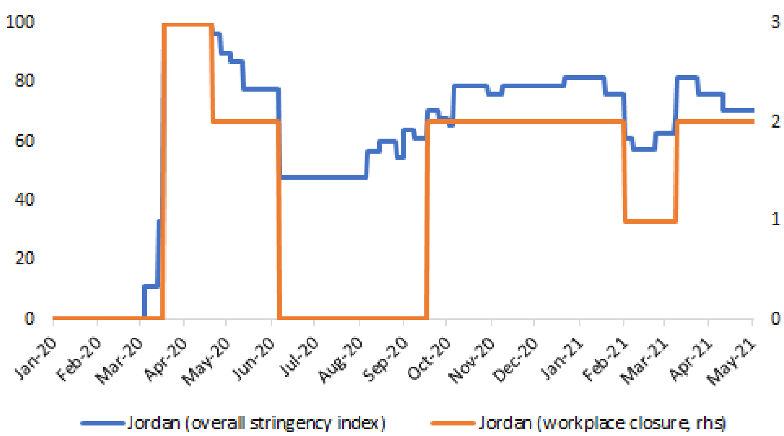
3.3 Response to the pandemic

3.3.1 Jordan

Beginning on March 21 of 2020, the government of Jordan put in place rigorous measures to contain the spread of COVID-19, including the closure of businesses and work stoppages for all but essential economic activities, as well as non-essential movement restrictions. In an effort to stem job losses, Defense Order #6 (DF6), also issued in the spring of 2020, prohibited layoffs by registered private firms, unless they were "frozen" or permanently closed. Because many workers still experienced significant wage reductions and others suffered from the cessation of their employers' operations, Jordan also launched subsidy schemes—the most important of which started in January of 2021. According to the CFUWBES data, despite DF6, even firms remaining in business reduced their workforce, whether through temporary furloughs or permanent layoffs.[11] In fact, we find that job losses at firms remaining in operation account for approximately 63 percent of the total.

While some of the lockdown measures were partially eased on May 3, 2020, international commercial flights remained suspended until September 8, 2020. Moreover, during the last quarter of 2020, Jordan experienced a resurgence of COVID -19 cases, resulting in other restrictions to economic activities. Health impacts have also been devastating.

Figure 1: Stringency Index in Jordan, 2020-2021 (higher means more stringent)



Source: Oxford COVID-19 Government Response Tracker, Blavatnik School of Government, University of Oxford. Note: For workplace closure index, 1 means "recommend closing", 2 means "require closing for some sectors or categories of workers", and 3 means "require closing for all-but-essential workplaces".

To mitigate the economic effects of the crisis, the government has implemented a set of fiscal and monetary measures designed to provide liquidity to businesses and social protection to the population. This package has included cash support programs for vulnerable households, wage subsidies for workers in affected sectors, including a wage subsidy of 50 percent of employees' salary in the tourism and transportation sectors,

[11] The distinction between furloughs and layoffs was part of the standard questionnaire but was not asked in the first round of the CFUWBES for Jordan.

disbursement of unemployment benefits for workers on unpaid leave, and credit schemes for firms hit hard by the crisis (Gentilini et al., 2020).

Nonetheless, the Jordanian economy has been hit hard, contracting by 1.5 percent in 2020 (WDI, 2020). The unemployment rate began to climb, to 23.0 percent at the end of Q2-2020, while the labor force participation rate fell by 0.4 percent during this period (World Bank, 2020). According to the CFUWBES1, 26 percent of private formal firms in Jordan reduced their workforce by June 2020 relative to 2019, and 39 percent did so by the early winter (November 2020 and January 2021.) Firms experienced an average reduction of 52 percent in monthly sales compared to one year before, and only 10 percent of firms did not experience any reduction.

3.3.2 Georgia

The Georgian government declared a national state of emergency in response to the pandemic for the period between March 21 and May 22, 2020. Strict measures were imposed, including lockdowns of high-risk districts and businesses, school closures, and a ban on public transport and border crossings. To alleviate the socio-economic damage, the government introduced an assistance package worth GEL 3.4 billion (close to 7 percent of GDP). Assistance includes cash transfers to low-income households, self-employed, and informal workers who lost their jobs, unemployment benefits for workers who lost jobs,[12] and tax waivers, credit guarantees, interest subsidies and microgrants for the private sector.

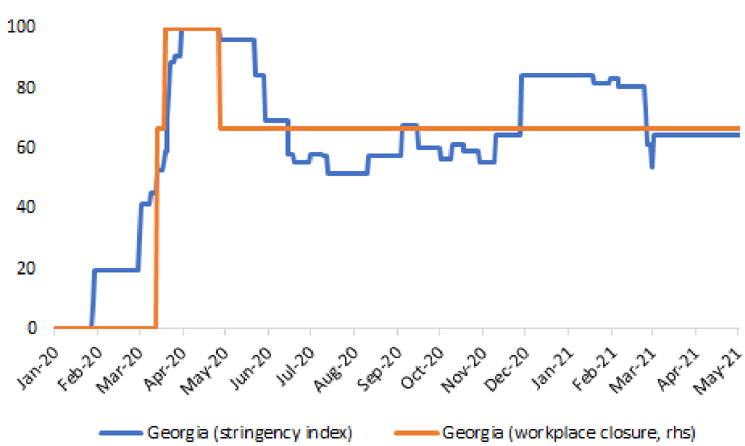
The pandemic nonetheless triggered a steep economic contraction of 6.2 percent in 2020 (WDI, 2020). The easing of measures in the summer of 2020 contributed to a significant

[12] People employed in the informal sector or self-employed who lost their jobs received a one-time assistance of 300 GEL. This was particularly aimed at those who applied for government assistance but were refused. The government allocated 75 million GEL to this program, reaching to 170,000 people received it.

second surge in COVID-19 cases later in the year, and Georgia temporarily found itself among the worst 20 countries in terms of the number of reported cases per million population. The government imposed a second strict lockdown from end-November to early February 2021, which helped reduce COVID-19 cases, and the economy started a gradual reopening in March 2021.

Georgia's unemployment rate rose sharply and reached 20.4 percent in the fourth quarter of 2020. According to the CFUWBES1, 25.8 percent of firms had reduced their permanent workforce by June 2020 relative to the end of 2019, 31.4 percent of firms by the time of the second wave of the survey conducted from November 2020 to January 2021. The percentage of firms reporting a loss in sales stood at 78.2 percent, and firms experienced an average reduction of 47 percent in monthly sales compared to one year before the interview.

Figure 2: Stringency Index in Georgia, 2020-2021 (higher means more stringent)



Source: Oxford COVID-19 Government Response Tracker, Blavatnik School of Government, University of Oxford. Note: For workplace closure index, 1 means "recommend closing", 2 means "require closing for some sectors or categories of workers", and 3 means "require closing for all-but-essential workplaces".

3.4 Causal Model

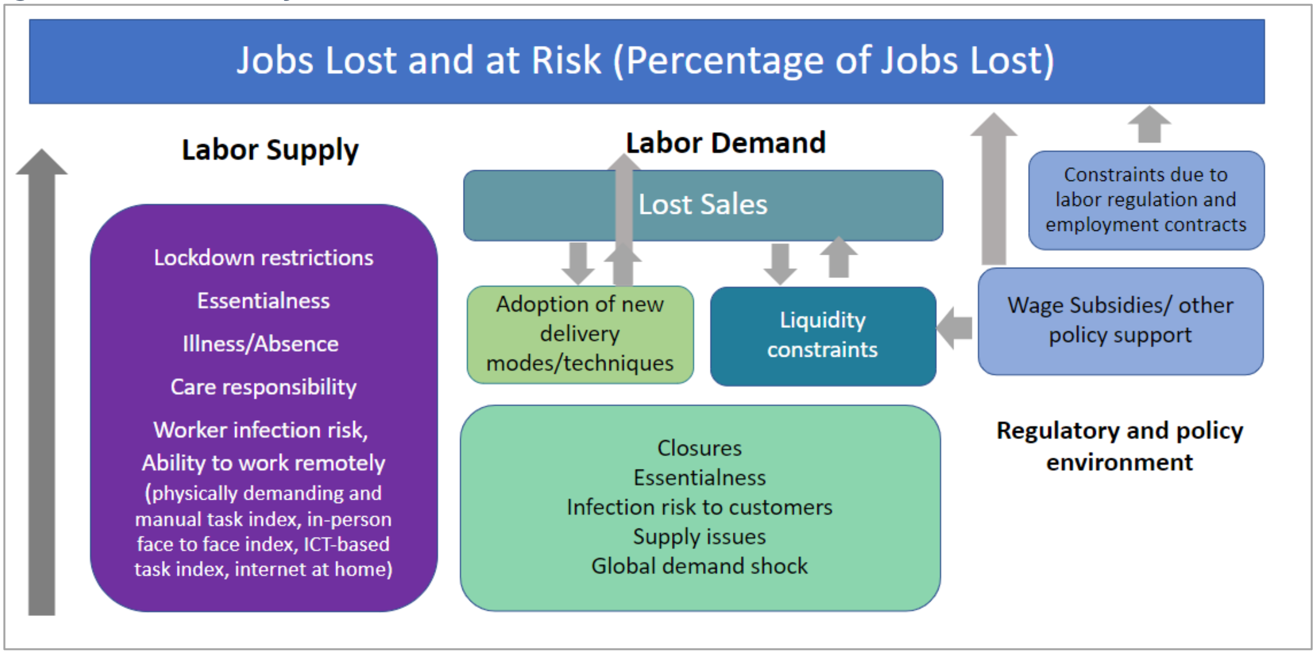
We use a simple model of job loss to inform our empirical specification. As depicted in Figure 3, it captures the role of potential factors and logical/hypothesized channels of impact, as well as interactions and potential endogenous factors. Labor supply and labor demand channels are shown as broad channels of impact on jobs, with causal influences on these listed underneath them in the figure. Separately from labor demand and supply, contractual and regulatory constraints can affect the level of job loss. Ideally, one would fully disentangle all labor supply and labor demand side channels, as this would provide additional insights important for policy and permit a more refined assessment of jobs at risk. Yet whether the demand or the supply of labor is more limiting to job outcomes can vary between workers, firms, locations, occupations, skill sets, and sectors. Moreover, some factors can affect both supply and demand. For example, firm closures due to COVID-19 restrictions and their exemptions due to "essentialness" operate on both, as they impede both transactions for which there is a market and the ability to go to work. Regardless of these complexities, we attempt to distinguish demand and supply factors as feasible. Our causal model can also be written in general equation form as follows:

$$J_i = J(LD(Q_i(D_i(\nabla_i), Clo_i, Ess_i, Ic_s, A_i(Z_i)), F_i(Q_i, Z_i), P_i), LS(Clo_i, Ess_i, Iw_s))$$

where job loss (J) of firm i is a function J of shocks to a firm's labor demand, LD_i, and labor supply to the firm, LS_i. LD_i is determined by a function LD of firm-specific shocks to sales, Q_i, which are affected by shocks to final output demand, D_i, COVID19 related closures, Clo_i, the essentialness of firm i's goods or services, Ess_i, input supply chain shocks (sc_i) and the firm's adaptation to new delivery technologies, A_i. A_i, is in turn affected by a vector of other firm or sector specific shocks and characteristics, Z_i. The firm's demand shock is a function of ∇_i, a vector of sector level shocks and unobserved demand shifters, as well as closures, essentialness, and infection risk to customers from consuming the good or service, Ic_s. The demand for labor is also potentially impacted by policy support received, P_i, and financial difficulties, F_i, which are affected by pre-COVID firm characteristics, Z_i . It is also potentially affected by technology adjustments, A_i and shocks to sales, Q_i.

Shocks to the labor supply to the firm, LS_i, are a function LS of closures and essentialness exemptions, infection risk to workers in the sector, denoted Iw_s, which depends in turn on the task content of a job (averaged at the sector level); in particular, the requirement of

Figure 3: Causal Model for Job Loss



face-to-face interaction, which augments infection risk, and the ability to work remotely, which mitigates this risk.[13] Labor supply would also vary according to an individual worker's home care requirements, illness, or other behavioral factors related perhaps to household wealth, unemployment benefits or other transfers. However, these individual-level situation variables, which may in turn relate to gender and age, skill level, socially conditioned preferences and possibly employer discrimination, are not observable at the firm level and are therefore are not part of our model.

[13] In practice, because the data used to construct infection risk do not distinguish between proximity to customers and proximity to other employees, we use the same index for both.

3.5 Econometric Model Specification

This theoretical model suggests the necessity of a multi-stage econometric model, with jobs lost in the final stage. We permit several variables to be econometrically endogenous, whether because of the possibility of reverse causality or of unobserved determinants of a regressor and the outcome variable, which can cause simultaneity bias to estimated coefficients. Regressors which we treat as potentially endogenous include the firm's change in sales (Q), its experience of liquidity problems (F), its share of workers working remotely (or from home) ($swfh$), and whether the firm expanded or adopted an online platform or new delivery mechanism (A). Simultaneity between changes in sales (Q) and jobs lost (J) may be especially important because unobserved factors, such as entrepreneurial ability, expectations about the future, or market opportunities, can affect both, and constraints to labor supply can affect production and sales. Sales (Q) may also be affected by financial/liquidity problems (F), and J and F are in turn affected by unobservable demand for the product or service / sales. We also treat as potentially endogenous firms' export share of sales, because the firm's ability to tap export markets may be affected by unobservable firm characteristics.

Further complicating the estimation is that for a significant percentage of observations (up to 40 percent) key variables are missing and some firms may not report all relevant variables, in some cases because they have closed permanently, all of which raises the potential of selection bias.[14] Since an understanding of causal relationships is key to

[14] There are two possible sources of non-response. First is that certain variables may be missing, and observations are missing across several key variables (sales, employment, and so forth). We reject the hypothesis that they are missing completely at random with a p value of .06 and .00 for Jordan and Georgia, respectively. In the case of Georgia, we do not reject the hypothesis that they are conditionally missing at random when taking into account characteristics of the firm, such as firm size (small/med/large), whether the firm was an exporter pre-covid, and percentage of foreign ownership. The second possibility is that firms were not obtainable. Overall, the non-response rate for Georgia is 12.4% in R1 and 13.6% in R2. There is no

designing policy, we endeavored to derive unbiased estimates of causal impact on jobs as a means to calibrate risks that policymakers may wish to consider. To address this combination of potential sources of estimation bias, we use the control function approach (see Newey et al., 1999), which entails including generalized residuals from first stage regressions to correct for simultaneity and/or selection bias. Selection bias is a concern if non-response to key survey questions for our analysis is not random. We include generalized residuals in later stages, including the inverse Mills ratio from a selection equation, whenever they are statistically significant. [15] We must adopt some identifying assumptions (or exclusion restrictions) to estimate proximate causal relationships. These are as follows: predetermined (pre-COVID) variables such whether the respondent to the COVID follow up survey had changed since the 2019 WBES , the firm's size category (captured by dummy variables), and experience of the firm's top manager (for missing observations/selection); the level of foreign ownership (for digital adaptation); foreign ownership and pre-COVID usage of banks for working capital or a line of credit (for subsequent liquidity problems and for the receipt of government support) [16]; the share of

indication that the firm was "unobtainable" in the implementation reports from Georgia. For Jordan, the refusal rate is 4.0% in R1 and 5.7% in R2. However, there are some firms classified as "unobtainable" in Jordan, which account for 2.2% in R1 and 8.8% in R2. No new firms were added to address attrition, and the sample frame is the same for the two rounds of CFUWBES.

[15] We elect a standard econometric approach to arrive at the best linear unbiased estimates of coefficients on explanatory variables. We experiment with variable selection by running multiple versions of the same equation. In theory, a T-test of the significance of an included regressor is a test of whether it should be included in the model. If not statistically different from zero, the variable has no explanatory power, and its inclusion would only reduce efficiency of the estimation. Therefore, in general, we prefer a parsimonious model. This increases potential applicability to other contexts and improves efficiency of the estimations. For some tables, we report insignificant regressors of interest, nonetheless. Generalized residuals that are not significant show that the correction is not a significant determinant of the outcome variable and should be excluded. This also reduces the inconvenience of bootstrapping standard errors when OLS could be used. Cross-validation is another method for model selection and provides the best linear unbiased predictor, but our main focus in this phase is to estimate and test the significance of various contributors to job loss. In practice, cross-validation would be computationally complex and impractical when there are multiple stages in the general causal model.

[16] In practice, we find that unobservable determinants of the propensity to receive policy support were not significant in later stages of the estimation.

the firm's workers with a university degree, the ICT-related task content of jobs in the sector, and firm-size (for the share of employees working from home), and exogenous global demand shocks for the change in the export share of sales.[17] There may be unobserved attributes, such as firm ability or opportunity, which would cause a violation of the assumptions that these variables are not correlated with unobservables in the later stage regressions. Given this possibility, we tested whether the excluded variables were significant in the final stages, and they were not.[18]

The regression model is therefore written as follows:

$$J_i = \alpha + \beta Q_i + \rho\omega_i + \forall X_i + \tau\mu_i + \epsilon_i$$

Where ω_i is a vector of potentially endogenous variables: self-reported financial difficulties (F), the use of new or expanded electronic platforms (A), and the share of work from home ($swfh$); X_i is a vector of exogenous factors such as infection risk to workers (Iw), policy support variables (P), and the pre-COVID share of the firm's workers on permanent contracts. μ represents a vector of control terms to correct for possible endogeneity bias arising from $Q, F, A, swfh$, as well as the inverse Mills ratio, and ϵ represents an i.i.d. error term. The equation for the percentage change in the firm's sales relative to the same month pre-COVID, is as follows:

---

[17] We cannot model firm entry and exit given data limitations. With respect to entry, the sampling frames were not refreshed with each round of the CRUWBES. Moreover, we cannot model firm closures as of round 1 within the same model structure as that used for firms in operation, because variables are not captured for those that have shut down. For example, some of those firms may have received wage subsidies or had supply chains disrupted after round 1, but this is not observed in round 2. Because we attempt to control for selection bias, whether due to non response or firm exit, we still in principle have unbiased impact estimates. Moreover, it does not appear that the inability to model firm exit and entry biases our aggregate results, given that in practice our forward-projected estimates without this aspect modeled match the CMMHH data well (see subsequent sections).

[18] First stage regression results are provided in Appendix 2. In Jordan, we found that missing values for key variables were more likely if the respondent was not the same, the firm was not medium-sized, and the top manager had less years of experience. In Georgia, having mixed or foreign ownership was associated with lower rates of missing values.

$$Q_i = \delta + \theta \check{X}_i + \varphi T_i + \sigma \mu_{ni} + \mu_{qi}$$

Where $\check{X}_i$ represents weeks temporarily closed due to COVID (Clo), infection risk (interpreted here as infection risk to customers, Ic), and whether the firm's supply of goods, materials, and inputs decreased, sc. T_i represents a potentially endogenous set of variables capturing the firms' adaptation to digital platforms (A) and the change in the export share of sales (Ex), the occurrence of financial difficulties, F, and the share of workers operating from home ($swfh$), and μ_{ni} represents a vector of estimated residuals from first stage regressions, indexed by n.[19]

Each of the first stage equations for financial difficulties (F), digital adaptation (A), share of workers working from home ($swfh$), and the export share shift (Ex), can be generally written as shown below, with the specific Z vectors as listed above and with the sector-specific proxy shock to sector demand denoted as p_s:[20]

$$F_i = F(Z_{fi}) + \mu_{fi}$$

$$A_i = A(Z_{ai}) + \mu_{ai}$$

$$swfh_i = \mathrm{sw}(Z_{wi}) + \mu_{wi}$$

$$Ex_i = Ex(p_s) + \mu_{ti}$$

[19] It is also possible that capacity utilization pre-COVID would cause firms to react differently to later sales losses. If firms were already operating at low capacity (whether due to adverse demand trends or prospective investment in capacity), they may be more financially strained during the crisis due to the carrying costs of fixed capital. For that reason, they may reduce their workforce more quickly or expand the workforce more quickly when sales improve than those operating at closer to full capacity. We could not test this hypothesis, however, given that over 50 percent of the observations of pre-COVID capacity utilization were missing.
[20] Some variables are defined at the individual firm level and others are observed at the sector level; sector indicators are not included in any of our regressions, as they would supplant other variables and make causal inference more incomplete.

Whenever results were unaffected, we used parsimonious specifications for these first stages, omitting some exogenous regressors in earlier stages that were not statistically significant, in order to retain more observations in the final stages. To ensure that the results were robust to this choice, we also ran the model with all later-stage exogenous regressors included in earlier steps. Results are not affected. For Georgia, the generalized residuals were uniformly insignificant in later stage regressions, so we reverted to OLS.[21] Full results of all final specifications are contained in Appendix 2 and key findings are presented below.

In the next section, we first report the results of the sales equation, followed by the results of the job loss equation. We then present "first stage" equation results, which are important to understanding the more primary determinants of sales.

4. Econometric Findings and Main Job Loss Risk Factors

4.1 Determinants of Changes in Sales

We find that there were some key determinants of changes in sales common to both countries that had a similar magnitude of impact in each. As shown in Table 4-1, those are (*i*) weeks of closures due to COVID; (*ii*) whether the supply of inputs decreased; (*iii*) and export shocks. The impact of weeks of closure was similar across the two country cases at approximately 2-4 percent of sales lost per week of closure (similar to or greater than the 2 percent of a year that a week represents). In addition, a disruption or reduction in the supply of firms' inputs drove a dip in sales of approximately 18 percent of sales (in the last completed month relative to the same month in the previous year) in both countries.

[21] Our process of model selection involved estimating many variations of the model, with different combinations of included regressors. We omit insignificant regressors (with the T test being a test of the validity of including a regressor in the model), and we check the stability of the rest of the estimates. We found the coefficient estimates to be generally stable.

Table 4-1 : Sales Equation Estimation Results, Jordan and Georgia

Dependent variable: sales change since COVID-19 outbreak (percent change year-on-year)	Jordan	Georgia
Temporarily closed due to COVID-19 (weeks of closure) (Clo)	-2.371***	-3.903***
	(0.542)	(0.572)
Total score of infection risk (higher = more risk) (Ic)	0.163	-0.241*
	(0.143)	(0.144)
Whether supply of goods, materials, and inputs decreased (1=yes) (sc)	-17.87*	-18.83***
	(9.745)	(5.692)
Change in export share of sales (percentage difference) (Ex)	0.323*	n.s.
	(0.195)	
Supplies of goods and materials decreased (1=yes) * change in export sales ($sc*Ex$)	-0.418**	n.s.
	(0.205)	
The firm had export sales in 2018 (1=yes) * global demand shock (yoy change of US and EU imports, with imputation)	-0.058	0.259***
	(0.111)	(0.073)
Started or increased business activity online (1=yes) (A)	n.s.	n.s.
Residuals from digital adaption equation	n.s.	n.s.
Observations	371	413
Adjusted R-squared	0.240	0.388

Note: ***p<0.01, ** p<0.05, *p<0.1. Robust standard errors in parentheses. In the case of Jordan, bootstrapped standard errors are reported. N.S. indicates that the variable was omitted due to the lack of statistical significance. Although not all variables found to be insignificant are included in the final specification, we include some in the table to aid the exposition.

Some other influences on the firms' sales shocks differed, as one might expect, between the two countries. In particular, in Georgia, infection risk significantly impacted sales, but we found no evidence that it did in Jordan. As shown in Figure 3, case counts remained low in both countries through the summer. However, behavioral responses may have varied due to the different levels of risk to the populations' health, given Georgia's older age structure.[22] The impact of export market shocks also differed: In Jordan, firms with a higher initial export share of sales did not necessarily fare better, especially if supplies were disrupted. However, Georgian firms that were exporting as of 2018 and that experienced less unfavorable global demand shocks were able to maintain higher sales, as shown above by the positive and statistically significant coefficient on the interaction term between being an exporter in 2018 and proxies for sector-specific global demand shocks.[23]

4.2 Primary Drivers of Job Loss and Risk

In the final stage of model estimation, the job loss equation, we examine the relationship between labor demand and supply shocks experienced by the firm and its change in permanent workforce levels. We regress the percentage change in the firm's permanent workforce on the percentage change in sales, Q, whether or not firms experienced financial difficulties, F, whether they received policy support (P), digital technology adaptation (A), the percentage of workers under permanent contracts (all on the labor demand side), the percentage of workers working remotely ($swfh$), and workers' infection risk (Iw), weeks of

[22] Percentages of the population by age ranges are shown below, according to the CIA Factbook:

	Percentage of Population by Age Range	
Age Range	Georgia	Jordan
0-14	18.4	33.1
15-24	10.9	19.8
25-54	40.6	38.4
55-64	13.2	5.1
65+	16.9	3.7

[23] For most sectors, the global demand shock variable is constructed using the year-on-year variation of aggregated US and EU imports of the corresponding category of goods from June 2019 to June 2020. To also capture the global shock in service sectors, particularly tourism, which is important for both Georgia and Jordan, the year-on-year variation in international flight arrivals from the first half of 2019 to the first half of 2020 was used to construct the variable. For non-tourism service sectors, the shock is constructed by combining the shocks in the transportation sector and in upstream goods sectors (The weights of transportation are generally assumed to be 0.2 for wholesale sectors, 0.1 for retail sectors, and 0.5 for transportation related sectors (e.g. auto sales), with the remainder -- .8, .9, and .5 for the related goods sectors).

closure (Clo) and essentialness (Ess).[24] We also included generalized residuals from earlier stage equations for Jordan, where these were significant, to account for possible

Table 4-2: Job Loss Equation Estimation Results, Jordan and Georgia

Dependent variable: jobs lost / permanent jobs (more positive means more jobs lost)	Estimated Coefficient (standard errors in parentheses)	
	Jordan	Georgia
Percent change in sales same month last year / since COVID (Q)	-0.434**	-0.430*
	(0.187)	(0.253)
Started or increased online or delivery activities (1=yes) (A)	1.401	-4.824
	(4.737)	(18.14)
Faced financial issues (1=yes) (F)	-1.707	-7.004
	(7.748)	(17.03)
Percentage of firm workers working remotely (percentage) ($swfh$)	-0.0660	0.00284
	(0.104)	(0.168)
Received other (non-wage subsidy) policy support (1=yes)	0.451	6.048
	(7.646)	(11.62)
Received wage subsidies (1=yes)	-7.357*	-8.203
	(4.456)	(22.23)
Percent of workers on permanent contracts in Dec18	0.0615	0.204
	(0.146)	(0.269)
Inverse Mills ratio	22.02~	n.s.
	(13.63)	
Residuals from sales equation	0.417**	n.s.
	(0.204)	
Constant	-24.36	-15.28
	(18.52)	(22.48)
Observations	564	424
Adjusted R-squared	0.082	0.019

*** p<0.01, ** p<0.05, * p<0.1; ~=significant in some bootstrap trials.
Note: n.s. indicates that the variable was omitted due to a lack of statistical significance.
Standard errors are bootstrapped for Jordan.

[24] Some regressors were ultimately excluded as they were not significant and had no effect on the other coefficient estimates.

simultaneity and selection bias (due to incomplete responses). Our controls for selection and simultaneity bias mattered only for our results in Jordan. [25]

Table 4-2 shows the main results of our preferred specifications for both countries. A number of variables primarily relating to labor supply issues that factored into early jobs-at-risk discussions were not statistically significant determinants of the actual level of PFPS job losses in Jordan or Georgia. First, "essentialness" (Ess) was not significant in any stage of the estimation; nor was the share working-from-home ($swfh$). Moreover, none of the sector-level task characteristics such as face-to-face, physical labor, or ICT intensity were significant in any specifications of the job loss equation (and so were removed from the final version).

Our results suggest that consumer demand conditions and breakdowns in the supply chain were the most decisive determinants of job loss in these countries. For every 1 percent decline in sales, firms reduced their permanent workforce by approximately 0.4 percent, all else equal. Despite the similar coefficients on key determinants of job loss, the ranking of factors by the magnitude of their average impact differs for the two countries (see Figure 6). In particular, in Georgia, the unexplained determinants of sales contributed positively to firms' employment levels, and the greatest negative impact on average came through infection risk, whereas the largest adverse impact was through unexplained declines in sales for Jordan. However, infection risk did not have a separate augmenting effect on job losses in Georgia, a finding that aligns with Georgian high frequency phone survey showing that very few workers claiming to have stopped working in order to reduce their infection

---

[25] In the equation to predict whether all key variables were available and estimate controls for non-response, we found that for Jordan the probability of completed responses was higher if the respondent to the COVID follow up survey was the same person as in the 2019 WBES; for medium sized firms (but not large ones); and for managers with more experience in the sector. For Georgia, full response probabilities were not related to any of these variables. Unfortunately, we were unable to control for non-response there, because none of the Z variables were significant determinants of joint non-response.

risk (presented in Section 5.3.2 below). Both had similarly sized impacts of closures, which simultaneously affected labor supply and production (i.e., the supply of goods and services). Since we control to the extent feasible for firm-specific supply side issues (liquidity, endogenous labor supply, supply chain disruption), we infer that unexplained sales shocks are due largely to unobserved product demand shocks.[26] Supply disruptions had the third greatest effect on average in both countries. The offsetting effects of wage subsidies and a shift to export markets had relatively small impacts in preserving jobs.

Figure 4: Daily Case Counts per Million Population, Jordan and Georgia

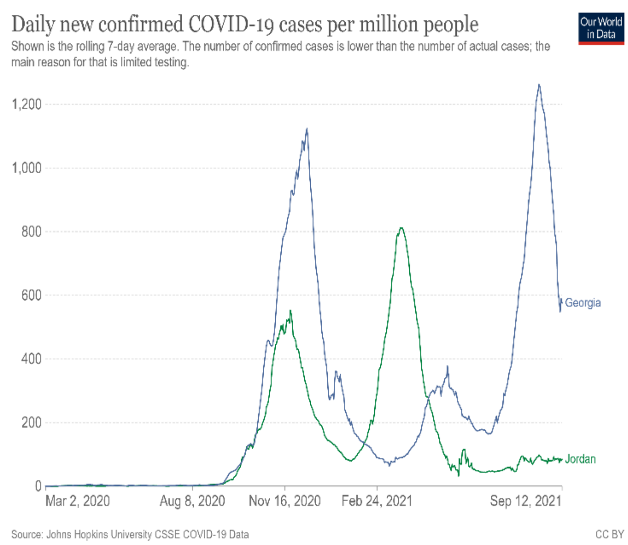
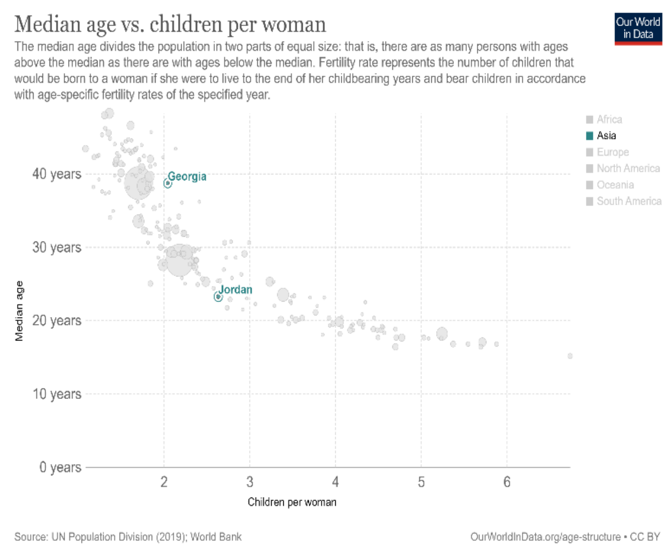


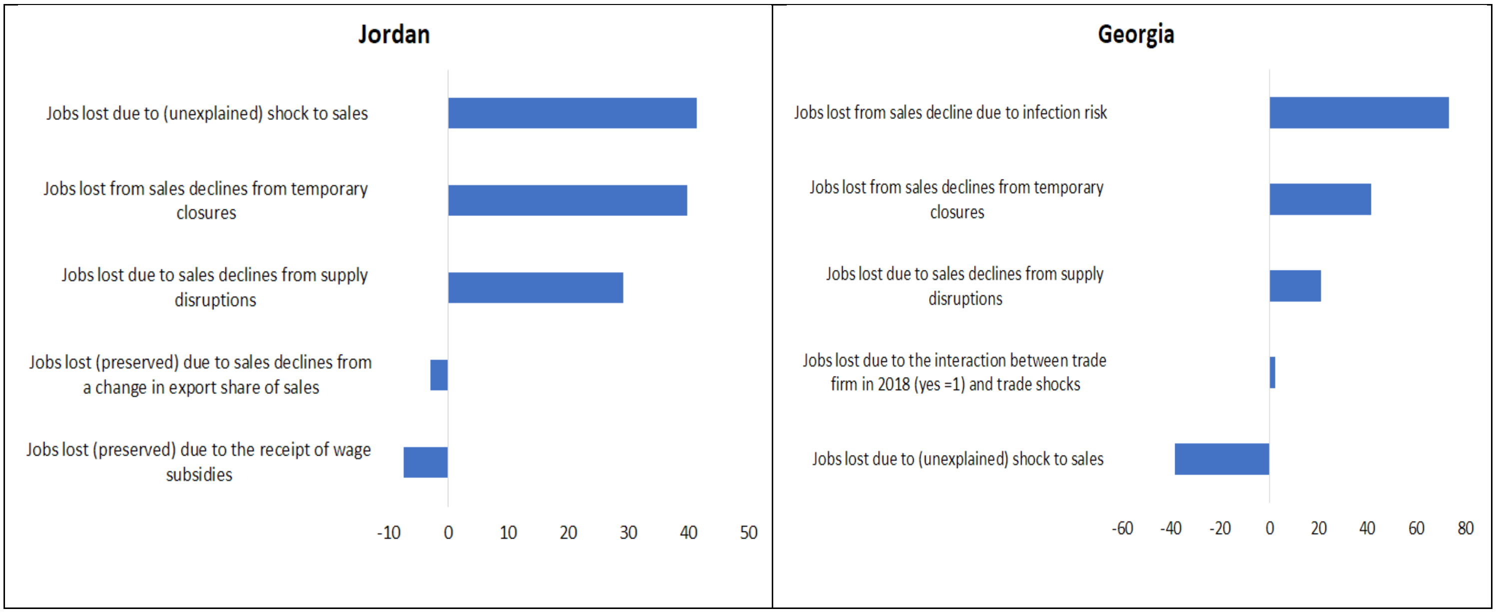
Figure 5: Median Age of Populations, Jordan and Georgia



Source: Our World in Data

[26] It is to be expected that large component of sales shocks is unexplained, because we demand patterns are likely to have shifted in ways that are not possible to capture empirically with the data available.

Figure 6: Contributing Factors to Jobs Lost (Average Percentage Effects on Total Jobs Lost)



Source: Authors' calculations

Using our empirical approach, we find no clear evidence that for firms still in business the inability to produce and sell goods due to financial constraints *per se* was a significant constraint to worker retention: we could not reject the null hypothesis of a zero coefficient on self-reported financial difficulties, conditional on declining sales. Financial stresses may, however, have led to permanent closures, even of otherwise viable firms, and we acknowledge that the variable on financial difficulties may capture them only crudely. [27] Supply side innovations, such as firms' adoption or expansion of digital and other sales or delivery methods, were also not statistically significant. Finally, we did not find that the permanency of labor contracts was protective even in the short run; the share of the workforce considered permanent did not affect workforce downsizing to a statistically significant degree in either country.

[27] We cannot model financial dynamics with our data. There is a correlation between those firms that closed and having reported financial stresses in the prior wave. However, this is not clear evidence of causation.

Perhaps surprising was that policy support to firms appeared to have had a limited direct role in preserving jobs as of the time of the CFUWBES wave 1 (CFUWBES1) survey. There were some differences between the two countries in this regard. In Jordan, firms whose workers received subsidized wages reduced permanent employees to a lesser extent. Yet we found no evidence that other forms of liquidity support did so. [28] In contrast, we found no clear evidence that any policy support extended to firms or their workers in Georgia played a role in reducing PFPS jobs losses, whether wage subsidies are examined separately or combined with other policy support in the regression. It may be relevant to note that Georgia did not subsidize the retention of workers per se, but extended a tax abatement on wage income. [29] Although in theory such an abatement would be equivalent to a wage subsidy (as long as wage income is taxed and under the unlikely assumption that wages are not downward sticky), such details as the level of support and eligibility for the program likely differentiate their impacts. [30] Although one should not discount the potential importance of policy support, which would have had welfare benefits and boosted local demand, our analysis suggests that over the medium run it had little direct impact on PFPS job losses in the face of declining sales and supply chain disruptions. In the next subsection, we present our findings on the determinants of key hypothesized drivers of sales and jobs.

[28] Other forms of policy support include cash transfers for businesses, deferral of credit payments, utility bills, rent or mortgage, suspension of interest payments, or rollover of debt, access to new credit, tax reductions or tax deferrals, and support (technical assistance or subsidies) for adoption of digital technologies. In Jordan, several unemployment benefit and insurance programs within the existing social security contributions were announced in April 2020. For example, if companies reduced wages by 50 percent, Jordanian or non-Jordanian employees received an unemployment allowance (a maximum of JD450 from their unemployment insurance savings). Employees in the tourism and transportation sectors registered with the Social Security Corporation also received a wage subsidy of 50 percent of their salary in the amount between JOD 220 and JOD 400 per month.

[29] Employees' salaries are either partially or fully exempted from income tax depending on the amount earned. (From April 2020 - May 2021).

[30] Depending on the relative elasticities of demand and supply of labor, a wage tax abatement could affect workers' supply of labor more than the demand for labor.

4.3 Determinants of Other Hypothesized Influence Variables

4.3.1 Financial Difficulties

Although we did not find evidence of a separate impact of financial difficulties, logically, one would expect that firms would be less able to adapt and ride out a crisis and less able to retain their permanent staff if they have a severe issue with liquidity. Based on our first stage estimation of the (assumed) exogenous determinants of experiencing financial difficulties, in both Jordan and Georgia firms were more likely to experience a financing constraint if they had relied on banks for working capital needs prior to the pandemic, reflecting differential reliance among business models on external sources of liquidity; and if they had more foreign ownership. However, at least as of June-July 2020, firms with different banking relationships and foreign ownership levels did not necessarily experience different levels of employee retention. The lack of significance may be due to the binary distribution of the variable and the lack of variation in it, as over 90 percent of firms claimed to experience these issues. Yet the experience of supply disruptions has a similar distribution and was found to be significant (See Appendix Table 15 and Appendix Table 16).

4.3.2 Ability to Adapt: Digital Solutions and Remote Work

In some economies, especially advanced ones, the availability of digital technologies is likely to have protected certain lines of business, firms, and workers during the pandemic, expanding or retaining communication with customers and making work from home possible. However, our analysis produced no evidence that in our two UMIC's, firms with higher shares of workers at home ($swfh$) were better able to mitigate firms' sales shocks during COVID-19 or the resulting magnitude of job losses. [31]

[31] In a small fraction of the specifications tried, the share of workers using ICT was negatively related to job loss, but this result was very sensitive to the inclusion of insignificant regressors.

On the supply side of the labor market, the ability to work from home (WFH), has been posited as an important determinant of jobs at risk, at least during mandatory firm closures (e.g., Hatayama et al., 2020). To test whether firms downsized less when their sector occupational structures were more conducive to working from home, we estimated the determinants of firms' share of workers working from home, $swfh$. In particular, we examined the role of physical demands, face-to-face interaction, and level of ICT use in a job, as well as the share of workers with internet at home according to the latest labor force data, averaging across occupations by sector. [32] Our results show that the ICT task index was statistically significantly related to firms' $swfh$ for both countries. However, the physical demands and in-person face to face indices of sector occupations were not significantly related to $swfh$ in either one. Measured internet use at home was insignificant for both as well, possibly in part because data on internet use was not sufficiently current. The index WFH (proposed by Hatayama et al., 2020) was statistically significantly related to $swfh$ as well, due to the component ICT use. The physical demands and face to face components of the index have (smaller, insignificant) coefficients of the expected sign as well. These results suggest that an empirically based measure of the risk of being unable to work from home would weigh each of these components differently than was done early in the crisis, at least for some upper middle income countries. Moreover, in addition to the occupational characteristics, we found that $swfh$ in Jordan was positively affected by the share of workers with university degrees and was higher for large firms (Table 4-3). In Georgia, $swfh$ was significantly higher for medium and large firms but was not related to the share of employees with tertiary education, possibly because of that country's high percentages of post-secondary-educated PFPS workers.

[32] Household internet usage was likely very high for PFPS workers by the time COVID hit. For the populations as a whole, 67 percent had internet access in Jordan in 2017 and 73 percent for Georgia in 2020.

We conclude that where greater ICT use for delivery, work, and other business functions was an option, it expanded easily in these countries and that without that option, more jobs would likely have been lost in the short run. However, on net over the medium term, firms had to maintain sales levels if they were to sustain their workforces, wherever certain workers performed their duties. Although some jobs can be done remotely within a firm, only limited services firms can operate fully remotely, and without the necessary labor contributions of key occupations and without adequate levels of demand, this ability does not translate to job retention in all sectors. Therefore, ICT options had limited explanatory power in their firms' ability to maintain sales. ICT-based work may have saved jobs for female workers who may have seen increased care responsibilities as schools closed. However, as discussed above, for the countries and sectors examined here, the ability to work from home was not a significant influence on the scale of formal firms' net adjustments to their permanent workforce. This also suggests that in analyzing job market dynamics more generally, it is important to consider the necessary combination of tasks/occupations within a firm and the complementarities between them.

Table 4-3 : Determinants of Share of Workforce Working from Home, Highlights

Dependent variable: share of firm's workforce working remotely	Jordan	Georgia
Percentage of permanent full-time workers with university degree	0.0901*	0.0101
	(0.0527)	(0.0205)
Firm size, categorical = 2, medium	3.566	7.174***
	(3.106)	(3.695)
Firm size, categorical = 3, large	9.264*	11.44***
	(4.856)	(3.799)
Physically demanding and manual task index (higher = more intense)	1.636	-1.309
	(1.149)	(2.492)
In-person face-to-face task index (higher = more risk)	-2.483	-1.908
	(2.202)	(3.819)
ICT task index (higher = less ICT use with low internet)	-4.999*	-6.503*
	(2.674)	(3.360)
Observations	436	535
Adjusted R-squared	0.145	0.042

Note: Full regression results reported in Appendix 2.

5. Projecting Job Losses and Validating the Method

In addition to understanding the causes of PFPS job losses, we propose to use our results for the following purposes: (1) assess the degree to which the identified causes can explain the realized distribution of job losses by demographic group; and (2) quantify job loss risk computations. To accomplish both, we therefore project estimated job losses at the firm level onto labor force survey data for the first round of data (CFUWBES1) and apportion realized outcomes to groups of workers. Then, since risks are inherently a forward-looking concept, we predict job losses into the near term future using a subsequent round of the CFUWBES (CFUWBES2) and then compare the predictions to real time survey data for Jordan, where such data were available. There is a methodological tradeoff between prediction and inference as it pertains to model selection.[33] However, since our claim is that understanding causes is important to assigning risk levels, and to maintain internal consistency and simplicity, including for usability in other contexts and countries, we elect to use our inference model for prediction.

5.1 Projection Method

With our econometric estimates in hand, the next step of our method is to translate model- predicted job losses ("modeled") from the CFUWBES1 to projected job losses for the population of PFPS workers as identified in the labor force surveys as follows: First, we use the statistically significant factors for job loss reported in Section 4 above (from the Job Loss equation) to predict job losses for firms still in operation as of round 1 of the CFUWBES. For comparison purposes, we also report results using simple CFUWBES survey means ("survey-measured"). For job losses at permanently closed firms, given data

[33] For example, prediction models may be selected on the basis of cross validation methods, and where dimensionality reduction is required, through machine learning methods.

limitations we must use a more information-limited method. Ideally, one would augment the econometric modelling of job losses with a firm entry and exit equation. However, using the CFUWBES data, it was not possible to model these dynamics in a manner separate from the selection equation method used because new firms were not sampled, and very few of the questions relevant to the drivers of job loss or jobs at risk were asked of permanently closed firms (in either round).[34] Therefore, we had to adopt a few simplifying assumptions to account for such closures: (1) that sales for permanently closed firms had fallen to zero; (2) that the coefficient on sales in the job loss equation was equally valid for permanently closed firms (even though job losses cannot exceed 100 percent); (3) that newly entering firms had a negligible impact on net PFPS jobs; and (4) that the effects of the other significant variables in the job loss equation (which are not observed for these firms) were swamped by the drop in sales to zero for permanently closed firms. Unfortunately, there is no avoiding such admittedly strong assumptions in the absence of more complete data.

Once we have estimated job loss levels by sector, we must next adjust the proportion of job losses by occupational category. We consider it unlikely that firms adjust their staff levels for each occupation in equal proportion as they adjust their overall workforce levels. Some types of labor input are "fixed" and others "variable." Unfortunately, there is a substantial disparity in the level of details on occupational categories in the WBES and LFS surveys. That is, the WBES survey asks only about "production" and "non-production" workers, whereas the LFS asks about occupation and job content.[35] We attempt to

[34] Firms that had closed permanently only answered section H questions in CFUBWES, which include closed year/month, whether they implemented certain measures before closure, and whether the firm is expected to reopen in the future.

[35] These questions are intended only for manufacturing firms, but some firms with main products being services also answered the questions. In Jordan, the number of service firms that reported production/non-production workers is 55, while in Georgia, where we used larger sector aggregations for these estimates, only 7 service firms reported such information.

estimate the share of job losses in each country by workers we designate as "fixed input" (non-production) employees and "variable input" (production) employees using the country-specific pooled (2013 and 2019) WBES data. We estimate a set of sector-specific polynomials relating the number of production to non-production workers for each aggregated sector (See Appendix 2 for details) and then compute the ratio of losses by each group within the appropriate ranges for each sector.[36] Using these estimated polynomials, we find that the estimated ratio between production and non-production workers varies substantially over the range of employment levels and by industry. Utilizing these empirical relationships therefore in principle makes our prediction more accurate than one that implicitly assumes that losses occur in equal measure across tasks and levels of total employment. In practice, without this adjustment to occupational category, we find that we are less able to replicate the demographic distribution of realized job losses, especially by level of education and wage quintile.[37]

After assigning the resulting mean percentage job losses to PFPS workers represented in the baseline labor force survey by sector and occupational level, we compute, using LMPS survey weights, the percentage of PFPS workers projected to lose their job. In addition to the total rate of job loss, we compute the approximate percentage of PFPS job losses by sector of employment (relative to baseline), by gender, age, educational attainment, wage level and nationality.[38]

---

[36] We use the highest order polynomial for which the highest order term is statistically significant.
[37] We compared estimates with and without this adjustment only for Jordan.
[38] For Jordan, we apply the net job losses from CFUWBES1 to the employment structure in 2016. We attempted to reweight observations to match the composition by age, gender, and industry in the MENA Monitor Survey, which has a smaller sample and does not include all nationalities. We found that this does not change our results appreciably, so we prefer the simpler approach of using the sampling weights in the LMPS.

5.2 Validity Checks

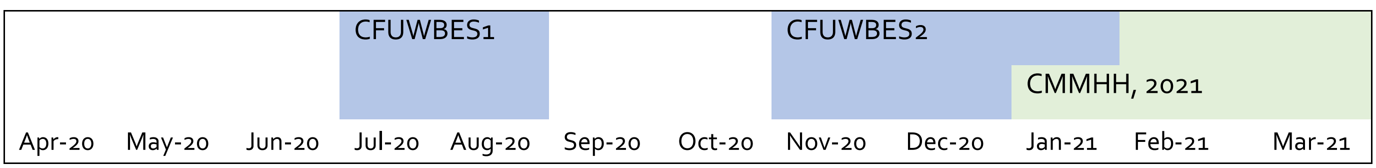
Having thus estimated PFPS job losses, we next assess the predictive accuracy of the magnitude and allocation by demographic groups of our modeled estimates. To do so, we use two bases for comparison. One is wave 2 of the CFUWBES. The second is labor force survey data collected at around the same time as this wave. In the first instance, we predict job losses using the model estimated using CFUWBES1 (Section 4) using the data on the influence variables from wave 2 to predict cumulative job losses for wave 2. We then compare these to the results we obtain when, instead of the model, we utilize a direct computation of average sector-firm-size job losses from CFUWBES2.[39] If the wave 1 coefficients were no longer valid by wave 2, one would see an important divergence in the results from these two approaches.[40] We do not see such a divergence. Nonetheless, this provides only an imperfect check on the ability of our estimated model to predict near term future job losses in wave 2. This is because the job losses directly tabulated using CFUWBES2 themselves may not be a perfect measure of the "truth." Certain sectors may be under-represented in the survey, and it may contain more noise than the model predictions (including due to outliers).[41] In practice, as detailed further below, we find that for aggregate job losses, the predicted and survey measured levels from CFUWBES2 match reasonably well for both countries, supporting the stability of the proximate causal relationships estimated in Section 4 over a short time horizon. When compared with actual covid period labor force monitoring data (discussed in the subsequent paragraph), we

[39] This approach can provide a short cut for assigning job losses to workers for situations in which such data are available and the objective is not to understand the drivers of job loss and risk or predict out of sample job losses.
[40] This could be due to the well-known Lucas critique. In particular, dynamic effects may alter causal coefficients over time.
[41] Moreover, both approaches to estimating job losses depend upon the modeled assignment of production versus non-production workers and the mapping to the LMPS.

generally find that the model-predicted estimates come closer to the actual observed groupwise distribution of job losses than the survey-measured projections do.

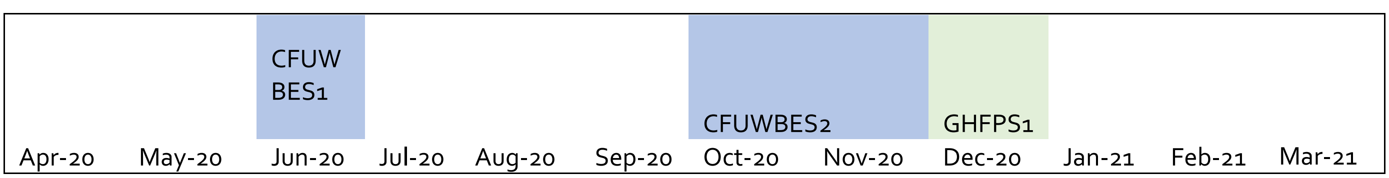
The second, more important validity check we perform is to examine the divergence between our model projections and a COVID-period monitoring survey of labor market impacts. For Jordan, we use the COVID-19 MENA Monitor Household Survey (CMMHH), conducted in January-March 2021 (See Figure 6, which depicts the surveys' relative timelines). The sampling frame for this survey differs from that of the LMPS survey in that it does not include "other" nationalities (non-Jordanian, Syrian, or Palestinian). In addition, the surveys utilized different definitions of industry categories, work arrangements, and employment types. In particular, the definitions used for "permanent" jobs varies. Finally, the survey's timing did not align perfectly with that of CFUWBES2. Therefore, one might expect some differences between the levels of PFPS job losses captured, Nonetheless, this comparison can provide an indication of the validity of our methodology.

Figure 7: Jordan: Timeline of Surveys



Source: CFUWBES Implementation Reports and COVID-19 MENA Monitor Household Survey Study Description.
Note: The CFUWBES asked employee levels at the end of the "last completed month", and the CMMHH asked individuals about their main activity in the "past month."

Figure 8: Georgia: Timeline of Surveys



Source: CFUWBES Implementation Reports and GHFPS round 1 main findings.
Note: The CFUWBES asked employee levels at the end of the "last completed month", and the GHFPS1 (Georgia High Frequency Phone Survey) asked individuals about whether they lost jobs due to COVID-19 since March 2020.

For Georgia, unfortunately, the available data do not permit us to perform the same type of validity check. As shown in Figure 8, there was a High Frequency Phone Survey (GHFPS) conducted in December 2020, just a month after CFUWBES2. However, this survey does not follow a sufficiently similar sampling approach to a labor force survey. The World Bank's high frequency phone surveys generally only capture data on the individual responding to the phone call, which in some countries has skewed samples toward the household head. In addition, the GHFPS does not permit one to net out job gains by other workers that may have occurred, as our methodology does (and as the CMMHH permits). Finally, the high frequency phone surveys do not contain the needed level of detail on work arrangements —employer types and contractual arrangement— to distinguish pre-COVID PFPS workers in the core sectors from other private sector employees. Notwithstanding these limitations, we attempt to learn what we can by comparing outcomes for private sector wage workers to our projections.

5.3 Aggregate Projection Results

5.3.1 Jordan

As shown in Table 5-1, using our methodology, for wave 1 (summer of 2020) we project the aggregate net rate of PFPS job losses in the core WBES sectors to have been 15.8 percent relative to the December 2019 baseline, which includes losses due to permanent firm closure of approximately 7.1 percent.

Table 5-1: Jordan: Job Loss Projections PFPS Jobs as a Percent of Pre-COVID Levels, CFUWBES Waves 1 and 2 and CMMHH, 2021

	As of Wave 1	Cumulative Wave 2	CMMHH 2021
Modeled Job Losses: Percent of PFPS jobs lost (relative to Dec 2019) as projected	15.8	25.2	N/A
Of which: Due to Permanent closures	7.1	9.4	N/A
Survey-measured job losses: Percent of PFPS Jobs Lost (relative to Dec 2019)	16.8	25.5	23.3

Source: Author estimates

Table 5-2 Jordan: Selected Potential Jobs at Risk Influence Variables, Means from CFUWBES

Variable	Wave 1	Wave 2
Temporarily closed due to COVID (weeks of closure)*	8.74	1.83
Percentage of firm workers currently working remotely (percentage)	8.71	2.82
Sales change (percent change year-on-year, relative to the same month in 2019)	-51.32	-49.71
Change in export share of sales (percentage difference from 2019 ES)	3.69	-2.62
Supply of goods and materials has decreased (1=yes, compared to the same month in 2019)	0.81	0.85
Started/increased online or delivery business activities (1=yes)*	0.57	0.13
Faced financial issues (1=yes)*	0.94	0.85
Received other policy support (1=yes)*	0.11	0.05
Received wage subsidies (1=yes)*	0.22	0.02
Infection risk (score) (0-300)	160.98	160.98

Source: CFUWBES.

Note: The baseline of the variables is 2019 unless otherwise noted: * Indicates that the baseline of the variable in wave 1 is "since COVID outbreak" and its baseline in wave 2 is "since wave 1" . Unless otherwise indicated, the statistics do not include data from permanently closed firms or firms that did not answer the corresponding survey question. Weights from each round are applied.

As the crisis wore on, job losses mounted. As shown in Table 5-2, Jordan's formal firms experienced broadly similar conditions by the time of the second CFUWBES wave as they had earlier. They reported only an additional 1.8 weeks of closures since the previous CFUWBES (June-July), when they reported 8.7 weeks on average, and a similar share of firms reported supply disruptions (85 percent). The share of sales comprised of exports fell relative to 2018, in contrast to the rise as of wave 1, and sales declines were of a similar magnitude as the previous round (50 percent). Meanwhile, a lower share of workers was operating remotely (2.8 percent on average relative to 8.7), and the share of firms newly engaging in online or modified (delivery) activities fell. A lower share of remaining firms still in operation was experiencing financial issues, despite the fact that fewer received policy support. By wave 2, we predict the cumulative loss of PFPS jobs to be 25.2 percent, including 9.4 percent from permanent firm closures (Table 5-1).[42] The survey-measured result is 25.5 percent, which is very close to the jobs at risk model prediction.

These estimates are also close to the net observed job loss rate of 23.3 percent in the CMMHH for the most similar group available in that data — formally employed private sector workers in the WBES sectors (PFPS workers) of either Jordanian, Palestinian, or Syrian nationality ("PFPS" workers). According to the CMMHH, 18.2 percent of these workers became unemployed; 2.8 percent were newly out of the labor force, and 2.3 percent had become employed as irregular workers or outside of the formal private sector. Even with the differences in the surveys' scopes, sampling approaches, and the questions posed on employment, the overall magnitudes of estimated jobs lost among formal private sector workers are remarkably similar. This provides support for our general approach to projecting aggregate job losses by linking firm-level modeled estimates and labor force surveys.[43] (Detailed results on "PFPS" workers from the CMMHH are reported in Appendix 2).

Table 5-3 Jordan: Rates of Net Job Loss by Type of Job, Percentage Change in Employment Levels from March to December 2020

Employer Type	Net rate of job loss
PFPS core sectors	23.3 percent
PFPS other sectors	17.5 percent
Private sector non-PFPS	-4.2 percent
Public sector	3.5 percent

Source: CMMHH

[42] The modeled incremental job losses between rounds were 9.3 percent, with 2.3 percent due to permanent firm closures.
[43] In the WBES, permanent workers are defined as those working fulltime in the formal private sector. In the LMPS, permanent workers are defined as private sector wage earners either reported to be permanent workers or to be fulltime and regular workers. In the MENA monitor survey, due the limitation in questions, we use regular and formal wage earners in the private sector as a proxy of permanent workers. We compare the share of permanent workers in total employment using our definitions and the results are very similar in the three surveys.

Since PFPS jobs represented only 42 percent of private sector wage jobs and a minority of all jobs in Jordan pre COVID, we use the CMMHH survey to examine whether the levels of job loss have differed across broad job types.[44] The CMMHH data on job and employment status transitions from before COVID to the winter of 2020 reveal that net levels of non-

Table 5-4 Jordan: Labor Market Impacts of COVID-19 in 2020-2021 by Employment Type in March 2020 (Percentage of those Employed Pre-COVID Reporting Impacts in the previous 60 days)

By pre-COVID employment status in 2020	Temporary layoff/ suspension (without pay)	Permanent layoff/ suspension	Reduced hours	Reduced pay	Delay in wage
PFPS	5.7	15.1	14.1	10.9	15.8
Private sector formal non-permanent workers	14.1	20.6	20.4	18.5	28.6
Private sector informal workers	18.9	19.3	21.0	23.6	23.3
Public sector workers	3.2	2.3	18.6	4.7	4.4
Total	8.8	10.9	18.3	12.2	13.4

Source: CMMHH Jordan, 2021

Note: These numbers do not reflect net job losses or gains by type of employment, reported above for the period since March 2020, because they are not offset by job gains. The question asks: "In the last 60 days, have you experienced any of the following because of Covid-19/coronavirus or related restrictions? (Enumerator: read all responses one by one and mark all that apply)".

"PFPS" jobs were much better sustained than those of PFPS jobs. Job losses persisted into the winter, accelerating for non-PFPS workers slightly more than for PFPS ones to a higher level during the 60 days prior to the CMMHH survey. As shown in Table 5-4, 20.6 percent of temporary workers in the formal sector and 19.3 percent of informal workers were permanently laid off or suspended without pay relative to 15.1 percent of PFPS workers. Still, on a net basis, informal and temporary jobs in the private sector actually increased, as

[44] CMMHH (2020). Just prior to the pandemic, 20.6 percent of employed individuals of working age in Jordan were employed in PFPS jobs, representing 42 percent of private sector wage workers. In addition, 37.6 percent of employed individuals worked for a public or government entity;2.2 percent worked irregularly but in formal work arrangements. Many (26.1 percent) worked informally, whether in a regular or irregular job, and 12.9 percent were self-employed. Recall that the survey excludes "other" nationalities. In 2016, this percentage was 22.5 (LMPS 2016), and slightly more when all nationalities are included.
The numbers reported in this paragraph differ from those reported in Section 3.2 above, because these do not include "other" nationalities, for the purposes of comparability with the CMMHH.

some workers were able to transition to them to post a net gain in such jobs of 4.2 percent, as workers entered the labor force, moved from unemployment, and found such work after losing PFPS and other jobs. In addition, formal private sector jobs were lost at a slower rate outside of the core productive sectors included in the CFUWBES than PFPS jobs, at 17.5 percent (relative to 23.3 percent). The public sector saw an estimated net job loss rate of 3.5 percent (Table 5-4).

5.3.2 Georgia

Georgia experienced a similar level of job losses early in the pandemic as Jordan, according to our estimates. As shown in Table 5-5, our model estimates the rate of PFPS job losses in the core WBES sectors of 19.0 percent by July 2020, which includes jobs lost in permanently closed firms of only about 0 percent. However, unlike in Jordan, as shown, by the time of the CFUBWES2, Georgia's PFPS jobs had rebounded, producing a predicted cumulative 5.9 percent rate of loss relative to December 2019. Permanent firm closures were associated with a job loss rate of only 1.0 percent. Although the modeled and survey-measured estimates are not as close as they were for Jordan, our prediction model does a reasonable job of matching the aggregate survey-measured job losses of 7.8 percent for that wave.

Table 5-5 Georgia Job Loss Projections PFPS Jobs as a Percent of Pre-COVID Levels

	As of Wave 1	Cumulative Wave 2
Modeled Job Losses: Percent of PFPS jobs lost (relative to Dec 2019) as projected	19.0	5.9
Of which: Due to Permanent closures	0.0	1.0
Survey-measured job losses: Percent of PFPS Jobs Lost (relative to Dec 2019)	18.1	7.8

Source: Authors' calculations.
Note: The post-COVID survey is not directly comparable to the projected jobs lost as it does not contain enough variables to separate PFPS workers.

Table 5-6 Georgia: Selected Potential Jobs at Risk Influence Variables, Means of CFUWBES Waves Rounds 1 and 2

	Wave 1	Wave 2
Temporarily closed due to COVID (weeks of closure)*	5.7	2.3
Infection risk (score) (0-300)	162.4	162.4
Percentage of firm workers working remotely (percentage)	3.8	2.9
Sales change (percent change year-on-year, same month in 2019)	-53.8	-28.2
Change in export share of sales (percentage difference from 2019 ES)	-0.7	-1.2
Supply of goods and materials has decreased (1=yes)	0.61	0.45
Started/increased online or delivery business activities (1=yes)*	0.21	0.17
Faced financial issues (1=yes)*	0.81	0.73
Received other policy support (1=yes)*	0.19	0.19
Received wage subsidies (1=yes)*	0.08	0.07
Interaction between whether had export sales in 2018 and trade shock	-5.1	-5.1

Source: CFUWBES.

Note: The baseline of the variables is 2019 unless otherwise noted: * Indicates that the baseline of the variable in wave 1 is "since COVID outbreak" and its baseline in wave 2 is "since wave 1". Unless otherwise indicated, the statistics do not include data from permanently closed firms or firms that did not answer the corresponding survey question. Weights from each round are applied.

It appears from the CFUWBES data that Georgian formal private firms were better able to remain in operation, boost sales, and re-absorb workers even under crisis conditions than their Jordanian counterparts. Between waves 1 and 2, they reported an additional 2.3 weeks of COVID-related closures on average and a lower share of workers was working remotely than before (2.9 percent). Moreover, the percentage of firms receiving policy support remained flat. However, there was a modest improvement in the share of firms reporting recent supply disruptions, with a decline from 61 to 45 percent. Crucially, sales rebounded between the two waves of the CFUWBES to a year-on-year decline of 28.2 percent, up from a 53.8 percent drop for wave 1. Whether due to greater ex ante resilience, better input and output market linkages, or more flexible labor markets, Georgian formal firms were better able to bounce back and rehire PFPS workers.[45]

Unfortunately, it is not possible to directly compare our projected outcomes for PFPS workers with observations in the GHFPS, as this group is not distinguishable from other private sector wage workers in that survey.[46] One can find little indication from the GHFPS that, by December 2020, there was a recovery in private sector jobs overall. However, by the third quarter of 2021, Georgia's labor force participation rate (52.8 percent) surpassed its level in Q3 of 2012 (51.8 percent) and unemployment fell from its pandemic era peak in Q2 2021 (22.1) to 19.5 percent.[47]

Table 5-7 Georgia: Percentage of Jobs Lost due to COVID-19, by Employer Type, December 2020

By employment category	Due to business or job losses from COVID	To avoid exposure to the virus	Other reasons (Including non-COVID-related)
Public sector employees	3.9	0.6	12.4
All private sector employees	24.1	1.8	17.0
All private sector employees, core sectors	29.0		
Self-employed	27.2	3.1	29.8
Employers	33.9	0.0	4.0

Source: the COVID-19 Georgia High Frequency Phone Survey (GHFPS).
Notes: Definition: "Individuals who lost jobs because of job or business losses due to COVID-19": Those who had a job in March 2020 but don't have a job in December 2020 and answered that they stopped working because they lost jobs or no business because of COVID 19. Other reasons include contract end, retired, temporary absence, illness, family or child-care responsibilities, and lack of transportation.

As in Jordan, Georgia's labor market impacts varied greatly by the type and sector of job. Relatively few public sector workers faced jobs losses (an estimated 3.9 percent). Moreover, private sector waged workers fared slightly better than the self-employed: 24.1 percent of them lost their jobs due to COVID and were no longer working, versus 27.2

---

[45] This is despite the fact that Georgia's overall closures were higher in the period between waves 1 and 2 than Jordan's and overall stringency indices were similar (See Section 3.3).
[46] The HFPS does not contain variables permitting one to distinguish formal from informal jobs.
[47] Georgia LFS. https://www.geostat.ge/en/modules/categories/683/Employment-Unemployment

percent of the previously self-employed (Table 5-7).[48] Only and 1.8 percent stopped working due to the risk of exposure to the virus. If the GHFPS is taken as reliable, these data may indicate either that the rebound in jobs for core productive sectors captured in the WBES drew in different workers than those originally losing their jobs (with a net effect similar to our projected level) or that job losses were much more persistent for informal and temporary work.

Based on aggregate rates of job loss due to COVID-19, our comparisons for Jordan broadly validate the method we propose for quantifying the level of risk of job loss for PFPS jobs. An additional test of our methodology and its limits would be to see whether it can predict the realized distribution of net job losses across

Table 5-8 Jordan: Model-Predicted versus Survey-Measured Projections of Sector-Level PFPS Jobs Losses, Wave 1 / Summer 2020 (with permanently closed firms)

	Model-Predicted	Survey-Measured	No. of Observations
1. Chemicals	4.9	9.9	26
2. Food, drink, and tobacco	8.1	9.2	73
3. Garments	18.7	23.6	50
4. Hotel, restaurant, and transportation	17.8	17.0	118
5. Machinery, electronics, and construction	16.3	22.6	36
6. Metals and non-metallic minerals	7.6	2.8	14
7. Wholesale, retail, and other services	19.3	19.4	147
8. Wood, paper, publishing, and printing	16.7	15.6	21
Total	15.8	16.8	485

Data Source: CFUWBES1
A positive figure indicates jobs lost. Model-predicted estimates are based on projected jobs lost using a multi-stage model and the employment structure in LMPS. Survey-measured jobs lost are based on directly computed sector-average job losses. In both cases, to estimate the allocation of jobs lost to production and non-production workers, we use the 2013 and 2019 World Bank Enterprise Surveys for Jordan and estimate sector-specific Tobit polynomial models. The calibrated models are applied to estimate the numbers of production and non-production workers of the pre-COVID baseline and the COVID wave. Survey weights applied in all calculations.

[48] The figures include all industrial sectors.

different categories of workers that would have most likely held the jobs that were lost.

5.4 Projected Job Losses by Sector

In this sub-section we assess how well projections of job loss align across various methods and sources of data by sector of employment. Because neither survey (WBES and LFS) on which our job loss projections are based are representative at the sector level, we might not expect projections to be fully reliable at the sector level. However, since we must use sectors to link employers to labor force data, it is important to assess this dimension of our methodology. Unfortunately, there is no ideal way to do so. The model estimates may be closer to the truth than direct computations from the CFUWBES, and sector classifications differ from WBES to the CMMHH. These issues, combined with small sample sizes for certain sectors in the WBES, suggest extra caution when using WBES data to derive sector-specific job loss estimates.

5.4.1 Jordan

We first compare wave 1 results for modeled- versus survey-measured approaches. As shown in Table 5-8, the rate of job losses varies a great deal, for these sector categories between 5 and approximately 20 percent (*chemicals* and *wholesale, retail, and other services*,

Table 5-9 Jordan: Model-Predicted versus Survey-Measured Projections of Sector-Level PFPS Job Losses, Winter 2020 / Wave 2

	Model-predicted	Survey Measured
1. Chemicals	13.2	17.3
2. Food, drink, and tobacco	20.8	8.0
3. Garments	23.8	37.4
4. Hotel, restaurant, and transportation	25.8	27.2
5. Machinery, electronics, and construction	34.9	39.2
6. Metals and non-metallic minerals	13.9	6.8
7. Wholesale, retail, and other services	26.6	29.5
8. Wood, paper, publishing, and printing	27.3	7.3
Total	25.2	25.5

Data Source: CFUWBES2
A positive figure indicates jobs lost. Model-predicted estimates are based on projected jobs lost using a multi-stage model and the employment structure in LMPS. Survey-measured jobs lost are based on directly computed sector-average job losses. In both cases, to estimate the allocation of jobs lost to production and non-production workers, we use the 2013 and 2019 World Bank Enterprise Surveys for Jordan and estimate sector-specific Tobit polynomial models. The calibrated models are applied to estimate the numbers of production and non-production workers of the pre-COVID baseline and the COVID wave. Survey weights applied in all calculations.

respectively). The job loss projections from the survey-estimated projections deviate somewhat from our modeled projections, particularly for sectors with fewer observations, including *Chemicals*, *Garments*, and *Metals and Minerals*. However, the model broadly predicts which sectors report the most severe reductions in workforce as well as those with less than average declines.

A comparison of wave 2 predictions for all firms (permanently closed and operational) with survey-measured job loss projections (Table 5-9) shows a reasonable match for some sectors (*Chemicals*, *Hotel*, *restaurant*, *and transportation*, *Machinery*, *electronics*, *and construction*, *wholesale*, *retail*, *and other services*. The greatest disparity in terms of sector ranking is for *Food*, *Drink*, *and Tobacco* and *Wood*, *Paper*, *Publishing*, *and Printing*. On the whole, the model, which is based on wave 1 data produces a closer alignment to wave 1 survey-measured projections than we obtain when we use the same model to predict sector-level job losses forward to wave 2. This is somewhat to be expected as there may be new dynamics that emerge over time that affect the link between influence variables and employment levels.[49] Nonetheless, the risk factors identified in our model remain valid even if they are not perfect predictors.

Examining job losses by sector in the CMMHH using its distinct sector classification, we see a higher degree of cross-sector disparity in PFPS job losses than using the WBES categories. As shown in Table 5-10, the percentage of "PFPS" workers which were permanently laid off or suspended was highest for *manufacturing* (39 percent), *and accommodation and food services* (39.0), but were essentially nil in *construction and utilities* and *ICT* sectors (which are not categories in the WBES.) As shown, when individuals were asked about impacts in the past 60 days, they reported a high level of temporary or permanent layoffs relative to the total shown in column 1, confirming that job losses

[49] The mean absolute deviation / total rate of job loss is higher for wave 2.

mounted in Jordan over the course of the pandemic. There were also significant temporary layoffs and suspensions without pay in manufacturing, ICT, and transportation and storage over that 60-day timeframe. In construction, working hours were reduced and wage

Table 5-10 Jordan: Labor Market Impacts of COVID-19 on Core Sector "PFPS" Workers

	Net Jobs Lost Due to COVID since March 2020 (percentage of pre COVID jobs	***Experienced in the Past 60 Days due to Coronavirus or Related Restrictions?*** Temporarily laid off/ suspended without pay (Gross change)	Permanently laid off/ Suspended (Gross change)	Working hours reduced	Wages reduced	Delay in wage
By sector						
Manufacturing	39.1	10.8	29.7	7.4	4.5	9.8
Construction or utilities	0.0	0.0	0.0	33.2	0.0	56.2
Retail or Wholesale	17.3	3.1	14.7	11.0	12.6	18.9
Transportation and storage	16.2	8.2	16.2	23.8	15.5	20.0
Accommodation and food services	38.8	3.6	19.0	5.0	7.9	26.0
Information and communication	0.0	10.4	3.5	18.8	7.5	7.5
Other services	15.1	3.8	15.1	0.0	0.0	0.0
Total	23.3	5.8	16.7	11.6	8.0	18.7

Data source: CMMHH 2021.

payments were delayed in lieu of laying off or suspending workers. In every sector shown, a large share of PFPS workers experienced adverse employment impacts in the prior 60 days.

Although impacts were widespread, the sector- level disparity in impacts underscores the importance of assessing which sectors will experience the greatest downturns, given the specific nature of a crisis, when assessing jobs at risk. Clearly, sector-specific shocks have been key to the pattern of job losses in this crisis and are likely to remain so in future ones. Changing demand patterns, supply chain disruptions, and public health matters vary appreciably by sector. Therefore, the more detailed are the sectors captured in data sources the more accurately one can identify jobs (or workers) at risk.

5.4.2 Georgia

For Georgia, as with Jordan, the projected rates of job loss vary substantially by sector. As shown in Table 5-11, our method projects that by the summer (wave 1), PFPS workers in *Garments* had experienced the greatest job losses (33.4 percent), followed by those in *Hotel, restaurant, and transportation* (27.4 percent of workers), and *Wood, paper, and publishing* (26.8 percent). Workers in the chemicals sector are projected to have faced fewer job losses (6 percent of workers). In almost all cases, non- production workers experienced lower job losses in the summer than production workers in all the sectors except for garments (See Appendix 2). Overall, the model projects similar levels of job loss to the survey-measured projections approach, although there is a large disparity between them in three sectors: *Chemicals*, *Hotel, restaurant, and transportation*; and *Wholesale, retail, and other services*.

Table 5-11 Georgia: Percentage of Permanent Formal Private Sector Jobs Lost by Sector, Model Predicted and Survey-Measured Projections, CFUWBES1 (July 2020)

	Econometric Model Projections	Survey Measured	No. Of observations
1. Chemicals	6.0	30.3	7
2. Food, drink, and tobacco	7.7	13.2	98
3. Garments	33.4	44.4	8
4. Hotel, restaurants, and transportation	27.4	39.9	99
5. Machinery, electronics, and construction	23.9	18.9	54
6. Metals and non-metallic minerals; Plastic and rubber	8.4	5.2	40
7. Wholesale, retail, and other services	15.0	8.2	164
8. Wood, paper, publishing, and printing	26.8	17.5	14
Total	19.0	18.1	484

Sources: LFS 2019, CFUWBES1, WBES 2013 and 2019.
Note: A positive figure indicates job loss. Model-predicted estimates are based on projected jobs lost using a multi-stage model and the employment structure in LMPS. Survey-measured jobs lost are based on directly computed sector-average job losses. In both cases, to estimate the allocation of jobs lost to production and non-production workers, sector-specific Tobit polynomial models are estimated using the 2013 and 2019 WBES. All calculations are survey-weighted.

By wave 2, our projected sector estimates show a recovery for all sectors except *Garments* (see Table 5-12), which remained by far the hardest hit. According to the Georgia High Frequency Survey, conducted just after the CFUWBES2, among private sector workers, however, the greatest rates of job loss occurred for those previously employed in restaurants and hotels, 55 percent of whom reported being unemployed due to COVID-19. Job losses remained stark as well in *Wholesale and retail trade*, which lost jobs for approximately35.6 percent of workers, compared to 10.1 percent in the construction sector.

Table 5-12 Georgia: Percentage of Permanent Formal Private Sector Jobs Lost by Sector, Model Predicted and Survey Measured Projections, CFUWBES2 (Winter 2020)

	Econometric Model Projections	Survey Measured	No. Of observations
1. Chemicals	6.2	-0.2	10
2. Food, drink, and tobacco	-2.3	6.9	107
3. Garments	22.4	44.3	8
4. Hotel, restaurants, and transportation	17.7	21.7	110
5. Machinery, electronics, and construction	6.1	8.0	56
6. Metals and non-metallic minerals; Plastic and rubber	-1.5	7.3	47
7. Wholesale, retail, and other services	2.2	0.0	188
8. Wood, paper, publishing, and printing	0.6	3.0	13
Total	5.9	7.8	539

Sources: LFS 2019, CFUWBES2, WBES 2013 and 2019.
Note: A positive figure indicates job loss. Model-predicted estimates are based on projected jobs lost using a multi-stage model and the employment structure in LMPS. Survey-measured jobs lost are based on directly computed sector-average job losses. In both cases, to estimate the allocation of jobs lost to production and non-production workers, sector-specific Tobit polynomial models are estimated using the 2013 and 2019 WBES. All calculations are survey-weighted.

Table 5-13 Georgia: Labor Market Impacts, Private Sector Workers, By Sector, Percentage of Pre-COVID Jobs

	Lost job because of job or business losses due to COVID-19	Stopped working to avoid exposure to the virus	Reduced income because of job or business losses to COVID-19	Reduced income due to reduced working hours
Industry/Manufacturing	16.3	0.0	60.7	11.8
Construction	10.1	0.0	53.6	27.3
Wholesale and Retail (Commerce)	35.6	7.2	67.5	22.2
Transport Services (Taxi, Bus, Truck)	19.7	0.0	55.6	25.2
Communications	14.7	0.0	41.2	22.5
Restaurants, Hotels, Bars, Cafes	55.8	1.5	81.7	11.6

Source: GHFPS.
Notes: Definition: "Individuals who lost jobs because of job or business losses due to COVID-19": Those who had a job in March 2020 but don't have a job in December 2020 and answered that they stopped working because they lost jobs or no business because of COVID 19. "Individuals who stopped working to avoid exposure to the virus": Those who had a job in March 2020 but didn't have a job in December 2020 and answered that they stopped working because they don't want to be exposed to the virus. "Individuals who reduced income because of job or business losses to COVID-19" Those who answered they decreased income due to job loss or closure of business. "Individuals who reduced income due to reduced working hours:" Those who answered they decreased income due to reduction in working hours.

5.5 Projected Job Losses by Demographic Group

Next, we examine the rate of projected PFPS job loss by the demographic characteristics of pre-COVID job holders. Because our method can only reflect how shocks at the firm-, sector-, and production/non-production worker levels play out in terms of jobs lost (or at risk), our demographic projections would not capture any effects of differential individual or firm behavior that may result in divergent outcomes by gender, age, or nationality. As such, a comparison of our projections with actual outcomes provides a sense of the degree to which pre-pandemic employment patterns alone would produce demographic differences and how much of those differences reflect behavioral factors.

5.5.1 Jordan

Gender: In both waves of the CFUWBES, our model projects a higher percentage loss of PFPS jobs for men than for women (see Table 5-14). For wave 2, the rate is 26 percent for men versus 19 percent for women. The survey-measured projection yields a more equal gender distribution of job losses than the model-based projection. However, the modeled prediction more closely aligns with the CMMHH data, which shows a 17.3 percent rate of

Table 5-14 Jordan: Comparison of PFPS Job Losses, Modeled, and Survey-Measured (including jobs lost due to firm closures), by Demographic Group

	CFUWBES1 Modeled	CFUWBES2 (Cumulative)		CMMHH
		Model-predicted	Survey-measured	
By gender				
Female	13.1	19.0	21.3	17.3
Male	16.2	26.0	26.1	24.8
By age group†				
below 25	15.5/15.3	25.6/26.9	24.6/24.9	23.1
25-45	16.5/16.3	25.2/24.9	26.3/25.6	20.6
above 45	11.1/14.3	21.3/24.3	23.9/25.9	38.3
By nationality				
Jordanian	14.7	23.8	24.2	21.2
Syrian	14.1	21.4	25.1	6.8*
Palestinian	13.1	28.2	20.7	40.5
Other	22.6	32.2	33.5	-
Total	15.8	25.2	25.5	23.3

Notes: The cumulative jobs lost by the time of CFUWBES2 is predicted by aggregating modeled jobs lost in CFUWBES 1 and the modeled incremental jobs lost from R1 to R2.
*May be unreliable due to small sample size.
†Age group results are shown assuming the same workers aged / assuming the age structure of employment is replicated between 2016 and 2020.

job loss for females and 24.8 percent for men. Female PFPS job losses were lower because in Jordan female PFPS workers tend to be highly selected among the female working population; pre-COVID, they were more likely to have higher education than male PFPS workers (see Table 5-15), and as we will see below, workers with higher education lost jobs at a lower rate. Therefore, our model would predict women retaining more of their (typically non-production) jobs than men. Of course, if one controls for educational attainment this may not be the case. Moreover, the female advantage does not carry over to non-PFPS workers. The CMMHH data reveals largely the reverse pattern for them: a higher percentage of female irregular workers became unemployed or left the labor force during under COVID-19 conditions than male ones (See Table 5-16).[50] By the first quarter of 2021, 35 percent of them were unemployed relative to 15.3 percent of males; and over 9 percent had left the workforce, whereas only 2.5 percent of men did so.

Table 5-15 Jordan: Private Sector Wage earners by Education and Gender pre-COVID

	PFPS (Percentages of all PFPS Employees)		Formal non-permanent wage earners (Share of PFPS workers)		Informal wage earners (Share of informal wage works)	
	Male	Female	Male	Female	Male	Female
Less than Basic	15.6	1.8	7.1	0.4	42.9	1.0
Basic Education	21.7	1.5	22.9	2.9	25.3	1.9
Secondary Education	12.7	1.7	10.5	3.8	15.6	1.1
Higher Education	30.2	14.7	29.7	22.7	10.7	1.5
Total	80.2	19.8	70.2	29.8	94.5	5.5

Source: LMPS 2016.

Age: As shown in Table 5-14 above, our method generates little age-related dispersion in job loss rates and therefore does not do well in predicting the large difference in job losses for older versus prime-age PFPS workers as captured in the CMMHH (38 percent versus 20 percent). These effects are most likely due to age-conditioned employer dismissals or labor

Table 5-16 Jordan: Percent of Non-Permanent Private Sector Workers Employed Pre-COVID No Longer Employed as of February 2021, by Gender

	Unemployed, 2021	Out of labor force, 2021
By Gender		
Female	34.8	9.2
Male	15.3	2.5

Source: CMMHH

[50] Although males comprised 70 percent of temporary formal private sector workers and 95 percent of informal workers pre-COVID, so women were relatively under-represented in these forms of work.

supply decisions.[51] Youth working in non-PFPS private sector jobs were disproportionately impacted as well. According to the CMMHH, by the winter of 2020/21, 25 percent of temporary workers under the age of 25 were unemployed and 5 percent left the labor force, relative to approximately 15.5 percent of other age groups becoming unemployed (Table 5-17).

Table 5-17 Jordan: Percent of Non-Permanent Private Sector Workers Employed Pre-COVID No Longer Employed as of February 2021, by Age Group

Age Group	Unemployed, 2021	Out of labor force, 2021
below 25	25.3	5.1
25-45	15.4	2.5
above 45	15.8	4.4

Source: CMMHH, 2021

Nationality: Conclusions based on reported nationality should be interpreted with caution due to the small sample size for national minorities and potential biases in data collection. Nonetheless, for Jordan, out method predicts the general pattern. As shown in Table 5-14, our model predicts higher rates of PFPS job loss for Palestinian and "other" workers, and lower rates of job loss for Syrian workers. This pattern is confirmed, indeed magnified, in the CMMHH data. However, the survey-measured projections do not project this general pattern. Once again, the model-based prediction gives a closer approximation to the demographic pattern of job losses observed in the CMMHH, lending support to that approach of assessing jobs at risk.[52]

5.5.2 Georgia

Gender: In Georgia, our model similarly projects impacts disfavoring men more than women (Table 5-18). The model shows a 17.4 percent rate of PFPS job loss for females compared to 20.0 percent for men in wave 1 of the CFUWBES and a 2.8 percent rate of

[51]Hypotheses one could examine with the available data are whether younger workers returned to education or became inactive at a higher rate; whether older workers withdrew from the labor force at higher rates than prime age workers (to retire).

[52] The CMMHH results must be considered tentative, because Palestinians and Syrians each represent a very small share of pre-COVID PFPS workers (approximately 3 percent each), and sample sizes for the CMMMHH were even smaller, making these statistics somewhat unreliable.

PFPS job loss for females compared to 7.9 percent for men in the Wave 2. However, the projected gender gap narrows when we utilize the survey-measured job loss rates.

Table 5-18 Georgia: Comparison of PFPS Job Losses, Modeled, and Survey-Measured (including jobs loss due to firm closures), by Demographic Group

	CFUWBES1 Modeled	CFUWBES2 (Cumulative)	
		Model-predicted	Survey-measured
By gender			
Female	17.4	2.8	6.4
Male	20.0	7.9	8.7
By age group			
below 25	19.4	6.8	7.1
25-45	18.3	3.7	6.6
above 45	19.8	8.4	9.4
By nationality			
Georgian	18.8	5.6	7.6
Azeri	22.6	17.2	12.8
Armenian	26.9	12.4	12.5
Other	16.2	2.0	3.2
Total	19.0	5.9	7.8

Sources: CFUWBES waves 1 and 2. Note: Jobs lost in the table are reported as cumulative. The cumulative jobs lost by the time of CFUWBES2 is predicted by aggregating modeled jobs lost in CFUWBES 1 and the modeled incremental jobs lost from R1 to R2.

These patterns are not consistent with those seen for the larger group of all private sector workers according to the GHFPS. In that data, 22.9 percent of men had lost their job between March and December 2020 due to COVID (and were not working in December 2020) in contrast to 40.8 percent of women (Table 5-19). More women also reported reduced income due to job or business losses than women while more men did so due to reduced working hours than women. [53]

[53] In both Jordan and Georgia, further research is required to fully understand gender disparities in the effects of the pandemic on labor markets. First, females are affected by intrahousehold resource allocation, meaning that they may suffer greater food insecurity, or non-monetary poverty even if their employment

Table 5-19 Georgia: High Frequency Phone surveys. Labor Market Impacts of COVID-19 by Gender, Percent of Private Sector Employees in March 2020

	Lost jobs because of job or business losses due to COVID-19	Stopped working to avoid exposure to the virus	Reduced income because of job or business losses due to COVID-19	Reduced income due to reduced working hours
Male	22.9	1.5	56.7	22.1
Female	40.8	4.3	77.1	15.6

Source: GHFPS

Age Group: Our method also projects, as in the case of Jordan, that the rate of job loss will be lower for prime age workers (aged 25-45) than for youth and older workers (and the survey-measured job loss projections were more even by age group as in the case of Jordan). Similarly, the GHFPS shows a 27.2 percent rate of private sector job losses for prime age workers relative to 44.1 percent for young workers aged below 25 (Table 5-20). Young workers also experienced greater rates of reduced income due to job or business losses.

Nationality: Our method projects divergent effects by nationality in Georgia as well. In particular, it estimates a greater rate of job loss for Azeri and Armenian than for Georgian workers, indicating that pandemic conditions would exacerbate nationality-based inequality.[54] We cannot report observed job losses by nationality, as the GHFPS does not capture data on or stratify by nationality.

income is not affected. Second, the analysis would capture relatively short-term effects of the pandemic as we rely on the data collected during 2020-21. Finally, the analysis doesn't reveal situations of under-employment and low-paying jobs among female workers.

[54] Available data from the 2018 Household Incomes and Expenditure Survey (HIES) show that prior to the pandemic the Azeri population was more likely to be poor than other nationalities in Georgia (World Bank, 2021) due to the types of firms, sectors, and occupations they were employed in.

Table 5-20 Georgia: Observed Labor Market Impacts of COVID-19 by Age Group, Percent of Private Sector Employees as of March 2020

Age Group	Lost jobs because of job or business losses due to COVID-19	Stopped working to avoid exposure to the virus	Reduced income because of job or business losses due to COVID-19	Reduced income due to reduced working hours
below 25	44.1	5.7	77.4	14.7
25 to 45	27.2	2.6	62.4	19.0
above 45	23.8	0.6	58.5	23.6

Source: GHFPS.

5.6 Projected Job Losses by Educational Attainment

For both Jordan and Georgia, our methodology produces a pronounced educational gradient, with projected job loss rates declining in the level of education.

5.6.1 Jordan

For Jordan, the educational gradient of job losses is similarly steep as that observed in the CMMHH. Job losses for "PFPS" workers with at most a basic education were on the order of 30 percent, whereas for those with higher education they were around 17-19 percent (Table 5-21), relative to our model's prediction of 29.9 and 17.4 percent, respectively. The

Table 5-21 Jordan: Distribution of PFPS Job Losses (Percentage of Jobs Lost) by Educational Attainment

By education	CFUWBES1 Modeled	CFUWBES2 Model-predicted	CFUWBES2 Survey Measured	CMMHH Survey Measured
Less than basic	19.3	29.9	28.0	33.9
Basic Education	16.2	28.3	25.0	29.9
Secondary Education	15.1	24.9	25.8	21.4
Higher education	13.3	17.4	24.2	19.4
Total	15.8	25.2	25.5	23.3

Sources: CFUWBES1, LMPS 2016, and CMMHH Jordan 2021.

model-predicted estimates for wave 2 were once again more in line with the CMMHH data than were the survey-measured numbers.

As with gender, the reverse pattern occurs when considering non-PFPS jobs, according to the CMMHH survey. In non-permanent or informal private sector positions, those with higher levels of education experienced a higher rate of job loss (Table 5-22). Yet the highest rates of withdrawal from the labor force occurred for those with secondary education.

Table 5-22 Jordan: Percent of Non-Permanent Private Sector Workers Employed Pre-COVID No Longer Employed, by Demographic Group

	Unemployed, 2021	Out of labor force, 2021
Less than basic	10.9	0.0
Basic Education	16.1	1.7
Secondary Education	19.5	9.3
Higher Education	24.9	4.8
Total	17.8	3.4

Source: CMMHH

5.6.2 Georgia

In Georgia, where a much higher share of the working age population has tertiary education, the rate of loss of PFPS jobs held by those with less than tertiary education in wave 1 was projected to have a modest gradient from 25.6 for primary schooled (or less)

Table 5-23 Georgia: Distribution of PFPS Job Losses (Percentage of Jobs Lost) by Educational Attainment

	Wave 1	**Wave 2**	
	CFUWBES1 Modeled	CFUWBES2 Model-predicted	CFUWBES2 Survey Measured
Primary or Lower	25.6	13.4	13.2
Lower Secondary	22.2	14.0	12.4
Secondary	21.2	11.6	10.8
University	14.9	-3.3	2.4
Post-Graduate	16.2	-1.9	3.7
Total	19.0	5.9	7.8

Sources: CFUWBES, LFS 2019

workers to 14.9 percent for university-educated ones. For wave 2 the gradient was similarly flat for those with less than a university education at 11-13 percent, and jobs held by those with more than a university degree were predicted to actually increase by the winter of 2020 compared to COVID-19 levels (Table 5-23).

According to the GHFPH, the general pattern holds, but with higher overall job losses: for all private sector workers, the reported rate of job loss was 50.9 percent for those with less than secondary education, and this falls to, 32.5 percent for those with university and 22.1 percent for those with post-graduate degree lost jobs (Table 5-24). The rate at which lower secondary- educated workers reported reduced income due to reduced working hours was nearly 50 percent, which was more than twice that of those with higher levels of education.

5.7 Projected Job Losses by Wage level

Many observers have predicted that the loss of jobs would be unequally shared, with the poor most greatly impacted by this crisis. Our method projects such unequal job losses in Jordan, but not in Georgia.

Table 5-24 Georgia: Labor Market Impacts of COVID-19 by Educational Attainment, Percent of All Private Sector Employees Experiencing since March 2020

Highest Educational Attainment	Lost jobs because of job or business losses due to COVID-19	Stopped working to avoid exposure to the virus	Had reduced income because of job or business losses from COVID-19	Reduced income due to reduced working hours
Lower Secondary	50.9	0.0	50.9	49.1
Secondary	30.5	3.2	69.5	19.9
University	32.5	0.0	55.0	15.0
Post-Graduate	22.1	2.1	54.2	22.0

Source: GHFPS.

5.7.1 Jordan

Our method projects that workers whose wages pre- pandemic were in the bottom quintile of the wage distribution in Jordan will have lost jobs at a rate of 19 percent by the summer of 2020, relative to 13.5 percent of those in the top wage quintile (Table 5-25). This unequal result is projected to have persisted into the winter, when 30.4 percent of jobs in the bottom quintile are predicted lost and 21.4 in the top.

These distributional predictions are not, however borne out in the CMMHH data, which shows the highest rate of job losses in the middle wage quintile (35.7 percent), and lower rates of loss at the bottom (9.7 percent) and the top (8.3 percent). Data on the occupational and pay structures within firms is likely needed to better identify the

Table 5-25 Jordan: Percentage of PFPS Jobs Lost, by Wage Quintile

National nominal hourly wage quintile	**Wave 1**	**Wave 2**		**CMMHH**
	CFUWBES1 Modeled	CFUWBES2 Modeled	CFUWBES2 Survey Measured	
Q1 (bottom)	19.0	30.4	30.1	9.7
Q2	16.6	26.5	25.5	26.7
Q3	14.0	22.6	22.6	35.7
Q4	14.1	21.0	23.5	17.1
Q5 (top)	13.5	21.4	25.0	8.3
Total	15.8	25.2	25.5	23.3

Sources: CFUWBES1, LMPS 2016, and CMMHH Jordan 2021

distributional dynamics of employment outcomes both during a crisis and during normal times of workforce adjustment. In developing countries such data are lacking.

5.7.2 Georgia

In contrast to Jordan, for Georgia our method projects declining job losses as wage levels rise. In the early stage of the crisis an estimated 21.1 percent of workers in the bottom wage range are projected to have lost their jobs and 16.4 percent of those in the top range (Table 5-26). By the winter, the top paying Georgian PFPS jobs are predicted to have completely recovered, whereas those jobs paying in the bottom range still are estimated to have experienced a cumulative job loss of approximately 11.2 percent. Because the GHFPS does not collect data on pre-COVID individual wages, we cannot provide any comparison to the larger population of private sector workers.

Table 5-26 Georgia: Percentage of PFPS Jobs Lost, by Earnings Interval

	Wave 1	Wave 2	
By monthly nominal net earnings interval LCU	CFUWBES1 Modeled	CFUWBES2 Modeled	CFUWBES2 Survey Measured
400 or less	21.1	11.2	10.2
401 – 600	19.1	7.5	8.6
601 – 800	18.4	4.0	6.1
801 or more	16.4	-3.0	4.3
Total	19.0	5.9	7.8

Sources: CFUWBES1 and LFS 2019.

6. Generalizability of Method and Findings

This paper investigates and compares the evidence on the drivers of job loss from two countries. It provides an evidence base for quantifying further risk of job loss and econometric results to inform the construction of a risk index. Our methodology holds the promise to be applied in a broader set of countries as well. Our comparative findings suggest some degree of generalizability of risk factors – and in particular the importance of closures, customer infection risk (especially when cases and transmission are high), supply chain disruptions, and other sector-specific shocks to consumer demand. Despite Jordan and Georgia's having different macroeconomic contexts and labor market structures, we find that they shared similar main drivers of job loss at the firm level, and the magnitudes of impact of those drivers was very similar for each.

Feasible approaches for broadening the application of our methodology and findings are likely to vary according to countries' data availability. Where sufficient firm-level and labor force data exist, analysts can follow the same steps to derive and utilize country-specific coefficients, considering all possible risk factors observed at the firm or occupation level, as shown in Column C of Table 6-1.[55] Alternatively, analysts can assign a job loss risk value

[55] A certain level of data sufficiency is required, such as some classification of production/non-production workers (or better), data on employment levels (baseline and a later period), and data on shocks to sales, at least.

based on a rescaled index using our coefficient estimates. Although it is never perfectly safe to assume external validity, in the absence of other country-specific evidence or data, where our coefficient estimates are similar for the two countries, it may be justified to use them for other middle income countries (Column A). Where firm or other data on initial shocks to sales (or its drivers, such as closures) exist, but data on other variables do not, the estimated effect of sales shocks can be linked to jobs in the latest labor force survey. As analysts adapt our approach or findings, they may opt to factor in other evidence as it accrues, for example, on the effects of different policy measures or behavioral responses (Column B). If data are also available on shocks to export demand, supply chain disruptions, and the magnitude of policy supports, these can be used to refine the quantified risks. Of all of the desirable data to utilize in such a prediction exercise, the critical pieces are panel data which capture sales and number of employees and a pre-crisis labor force survey.

Should one apply our method to other data contexts (Column C), care should be taken to consider any inconsistencies between a country's surveys in the classification of jobs, construction of samples, and wording of questions on employment status and transitions. Second, if data contain a considerable proportion of missing values, selection bias due to non-random non-response needs to be addressed. Additional caveats are important as well. For example, when relying on the information from developed countries such as O*NET from the U.S. or essential industry categories in Italy (in the absence of country-specific information), this may not necessarily reflect actual contexts in low- and middle-income countries.

Table 6-1: Possible Applications of this Paper to other Countries to Predict Job Losses, According to Data Availability

	A **Existing estimates are used to predict job losses**	B **Evidence from other contexts is combined with this evidence to predict job losses**	C **Apply full methodology (with data as per this paper)**	D **Ideal methodology**
Minimal data from relevant country	Data at firm or sector level on either (i) Sales changes or (ii) closures, export shocks, and supply chain disruption. Pre-crisis labor force survey.	Data at firm or sector level on either (i) Sales changes or (ii) closures, export shocks, and supply chain disruption. Pre-crisis labor force survey.	Panel firm survey, spanning pre- and during crisis period. Pre-crisis labor force survey containing occupation, task content, delineation of sector and type of employment.	Panel firm survey, spanning pre- and during crisis, including details on occupations of employees. Pre-crisis labor force survey containing occupation, task content, delineation of sector and type of employment.
Additional data or evidence required		Auxiliary empirical evidence of magnitude of impact of other factor in respective country, plus variable involved observed in firm survey.	Index of infection risk to customers and/or workers (from task content data, compiled by O*Net). Essentialness as defined by another country. Auxiliary data on global demand shocks.	Data on infection risk to customers and/or workers based on local infection rates. Essentialness as defined by the country. Auxiliary data on global demand shocks.

7. Conclusions

This paper analyzes the channels of impact from COVID-19 on the loss of permanent formal private sector (PFPS) jobs in two upper middle-income countries — Jordan and Georgia — and provides a methodology to estimate such job losses in other countries where there is no timely or nationally representative labor market survey to measure actual losses. We take into account labor supply conditions (essentialness of industries, workers' ability to perform their jobs from home, infection risks to workers) as well as labor demand shocks (firms' financial constraints, input supply constraints, customers' infection risk, global demand shocks, government support) to identify factors that have contributed most to job losses.

Our evidence suggests that labor demand shocks predominate overall in explaining job losses. We show that firms experiencing larger sales losses due to shutdowns, export demand shocks, supply chain disruptions, and in the case of Georgia, higher infection risk to customers, are likely to reduce their workforce more, with a sales-to-permanent workforce elasticity of approximately 0.4 in both countries studied. This suggests that although supply side interventions such as child care support or reduced payroll taxes may shore up welfare, carefully conceived policies to sustain aggregate demand, mitigate disruptions to the supply chain, and contain the virus would be more likely to preserve jobs. Determinants of labor supply, such as essentialness, the ability to work from home, and infection risk to workers were not statistically significant determinants of workforce reductions. There is also no evidence that firms that adopted online activities or delivery mechanisms retained significantly more PFPS jobs. Among occupational characteristics posited to affect the ability to work from home (such as more physically demanding task content or more face-to-face interaction), we found that only the ICT task content of jobs was related to the share of employees working from home. Although the ability to work from home may have been instrumental in preserving the labor supply of those workers with home care responsibilities, there is no evidence from these two countries that this ability impacted the overall level of net job losses. We find some evidence that wage subsidies had a small positive effect on job retention in Jordan, but we find no evidence in either country that other policy supports preserved jobs significantly. This underscores the importance of designing and scaling policy support measures carefully to preserve viable firms and jobs in the face of large demand shocks.

We find that our model-based method predicts the level of further job losses in the winter of 2020 fairly well, based on a comparison of predictions with a covid-period labor force survey for Jordan. Whereas it predicts the distributional impacts by gender, nationality, and educational attainment well, it fails to predict the differences by age group and wage level. Predicted and actual results show a greater rate of job loss for men employed in the formal private sector than for women and for those with less education. In addition, the rates of job loss by productive sector generally rank similarly to those observed, with some exceptions. We also document differences in the two countries' performance in restoring formal permanent jobs versus other types of jobs (informal, temporary, self-employment) in the private sector. In Georgia, with its stronger export market presence and more flexible regulation of formal employment, formal firms were able to boost sales and hire full time workers back. [56] Moreover, they did so at a significantly faster rate than appears to have been the case for informal firms, for which there was no clear sign of such a formal job recovery. In contrast, in Jordan, formal sector jobs continued to decline through the fall and early winter, and at a faster rate than informal and temporary jobs in the private sector.

Finally, we propose improvements to future firm surveys that would facilitate the ex-ante assessment and empirical understanding of jobs impacts, not only of future crises, but also of key labor market dynamics in non-crisis times. The rapid evolution of COVID-19 has highlighted the need for more detailed firm-level data (from formal and informal firms, ideally, with more than one employee) on their occupational structures and the contractual status of their employees. More granular data on the demographic composition of firms' workforces would complement labor force surveys and permit a more comprehensive

[56] Other drivers of this difference could be policy measures to boost local demand or better containment of the virus; however, the evidence we present herein is not consistent with either explanation. Another key difference may be Georgia's more educated workforce that is easier to train. However, this does not seem a likely explanation, since the rehiring rates are a function of a rebound in sales, rather than labor supply.

understanding of evolving labor market conditions and occupational structures , as well as the identification of the most vulnerable categories of jobs or workers from future crises and shifting demands for labor and skill.

References

Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics*, *189*, 104245. https://doi.org/10.1016/j.jpubeco.2020.104245

Albanesi, S., & Kim, J. (2021). *The Gendered Impact of the COVID-19 Recession on the US Labor Market* (No. w28505; p. w28505). National Bureau of Economic Research. https://doi.org/10.3386/w28505

Alfaro, L., Becerra, O., & Eslava, M. (2020). EMEs and COVID-19 Shutting Down in a World of Informal and Tiny Firms Laura Alfaro, Oscar Becerra y Marcela Eslava. In *Documentos CEDE* (No. 018193; Documentos CEDE). Universidad de los Andes - CEDE. https://ideas.repec.org/p/col/000089/018193.html

Alipour, J.-V., Falck, O., & Schüller, S. (2020). *Germany's Capacities to Work from Home* (SSRN Scholarly Paper ID 3579244). Social Science Research Network. https://papers.ssrn.com/abstract=3579244

Andersen, A. L., Hansen, E. T., Johannesen, N., & Sheridan, A. (2020). *Pandemic, Shutdown and Consumer Spending: Lessons from Scandinavian Policy Responses to COVID-19* [Paper]. arXiv.org. https://econpapers.repec.org/paper/arxpapers/2005.04630.htm

Aum, S., Lee, S. Y. (Tim), & Shin, Y. (2020). *COVID-19 Doesn't Need Lockdowns to Destroy Jobs: The Effect of Local Outbreaks in Korea* (No. w27264). National Bureau of Economic Research. https://doi.org/10.3386/w27264

Avdiu, B. and Gaurav, N. (2020). "When Face-to-Face Interactions Become an Occupational Hazard: Jobs in the Time of COVID-19." Policy Research Working Paper 9240. World Bank (May).

Avenyo, E. & Ndubuisi, G. (2020). Coping During COVID-19: Family Businesses and Social Assistance in Nigeria. COVID Economics, 1(51): 159–184.

Bachas, P., Brockmeyer, A., Harris, T., & Semelet, C. (2020). The Impact of COVID-19 on Formal Firms. In *World Bank Other Operational Studies* (No. 34393; World Bank Other Operational Studies). The World Bank. https://ideas.repec.org/p/wbk/wboper/34393.html

Baldwin, R. E., Weder, B. (2020). *Economics in the time of COVID-19* CEPR Press.

Balleer, A., Zorn, P., Link, S., and Menkhoff, M. (2020), 'Demand or Supply? Price Adjustment during the COVID-19 Pandemic', CEPR DP14907.

Bartik, A. W., Bertrand, M., Cullen, Z. B., Glaeser, E. L., Luca, M., & Stanton, C. T. (2020). How Are Small Businesses Adjusting to COVID-19? Early Evidence from a Survey. In *NBER Working Papers* (No. 26989; NBER Working Papers). National Bureau of Economic Research, Inc. https://ideas.repec.org/p/nbr/nberwo/26989.html

Bamieh, O. and L. Ziegler (2020). "How Does the COVID-19 Crisis Affect Labor Demand? An Analysis Using Job Board Data from Austria." IZA DP No. 13801, October.

Beck T, B Flynn, B. & Homanen, M. (2020). COVID-19 in emerging markets: firm-survey evidence. COVID Economics, Vetted and Real-Time Papers 38, July.

Betcherman, G., Giannakopoulos, N., Laliotis, I., Pantelaiou, I., Testaverde, M., & Tzimas, G. (2020). *Reacting Quickly and Protecting Jobs: The Short-Term Impacts of the COVID-19 Lockdown on the Greek Labor Market* (Policy Research Working Paper Series No. 9356). The World Bank. https://econpapers.repec.org/paper/wbkwbrwps/9356.htm

Beyer, R. C. M., Franco-Bedoya, S., & Galdo, V. (2021). Examining the economic impact of COVID-19 in India through daily electricity consumption and nighttime light intensity. *World Development*, *140*(C). https://ideas.repec.org/a/eee/wdevel/v140y2021ics0305750x20304149.html

Bonadio, B., Huo, Z., Levchenko, A. A., & Pandalai-Nayar, N. (2020). Global Supply Chains in the Pandemic. In *NBER Working Papers* (No. 27224; NBER Working Papers). National Bureau of Economic Research, Inc. https://ideas.repec.org/p/nbr/nberwo/27224.html

Boone, L. (2020), 'Tackling the Fallout from COVID-19', ch. 2 in R. Baldwin and B. Weder di Mauro (eds), Economics in the Time of COVID-19, London, CEPR, 37–44.

Bosio, E., Djankov, S., Jolevski, F., & Ramalho, R. (2020). Survival of Firms during Economic Crisis. In *Policy Research Working Paper Series* (No. 9239; Policy Research Working Paper Series). The World Bank. https://ideas.repec.org/p/wbk/wbrwps/9239.html

Buba, J. H. Uckat, Iacovone, L., & Medvedev, D. (2021). "Why did some countries' workforces fare better than others?" Blog. World Bank. June 1.

https://www.jobsanddevelopment.org/why-did-some-countries-workforces-fare-better-than-others-in-the-early-pandemic/

Casarico, A., & Lattanzio, S. (2019). What Firms Do: Gender Inequality in Linked Employer-Employee Data. In *Cambridge Working Papers in Economics* (No. 1966; Cambridge Working Papers in Economics). Faculty of Economics, University of Cambridge. https://ideas.repec.org/p/cam/camdae/1966.html

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., & Team, T. O. I. (2020). *The Economic Impacts of COVID-19: Evidence from a New Public Database Built Using Private Sector Data* (No. w27431). National Bureau of Economic Research. https://doi.org/10.3386/w27431

Cirera, X., Vargas Da Cruz, M. J., Davies, E. A. R., Grover, A. G., Iacovone, L., Lopez Cordova, J. E., Medvedev, D., Maduko, F. O., Nayyar, G., Reyes Ortega, S., & Torres, J. (2021). Policies to Support Businesses through the COVID-19 Shock: A Firm-Level Perspective. In *Policy Research Working Paper Series* (No. 9506; Policy Research Working Paper Series). The World Bank. https://ideas.repec.org/p/wbk/wbrwps/9506.html

Crossley, T., Fisher, P., & Low, H. (2021). The heterogeneous and regressive consequences of COVID-19: Evidence from high quality panel data. *Journal of Public Economics*, *193*(C). https://econpapers.repec.org/article/eeepubeco/v_3a193_3ay_3a2021_3ai_3ac_3as0047272720301985.htm

del Rio-Chanona, R. M., Mealy, P., Pichler, A., Lafond, F., & Farmer, J. D. (2020). Supply and demand shocks in the COVID-19 pandemic: An industry and occupation perspective. *Oxford Review of Economic Policy*, *36*(Supplement_1), S94–S137. https://doi.org/10.1093/oxrep/graa033

Delaporte, I., & Pena, W. (2020). *Working from Home Under COVID-19: Who Is Affected? Evidence from Latin American and Caribbean Countries* (SSRN Scholarly Paper ID 3610885). Social Science Research Network. https://papers.ssrn.com/abstract=3610885

Deshpande, A. (2020). The COVID-19 Pandemic and Lockdown: First Effects on Gender Gaps in Employment and Domestic Work in India. In *Working Papers* (No. 30;

Working Papers). Ashoka University, Department of Economics. https://ideas.repec.org/p/ash/wpaper/30.html

Dhingra, S., & Machin, S. J. (2020). *The Crisis and Job Guarantees in Urban India* (SSRN Scholarly Paper ID 3704143). Social Science Research Network. https://papers.ssrn.com/abstract=3704143

Dingel, J., & Neiman, B. (2020). *How Many Jobs Can be Done at Home?* (NBER Working Paper No. 26948). National Bureau of Economic Research, Inc. https://econpapers.repec.org/paper/nbrnberwo/26948.htm

e Castro, M. F., Duarte, J. B., & Brinca, P. (2020). *Measuring Labor Supply and Demand Shocks during COVID-19*. https://doi.org/10.20955/wp.2020.011

Fairlie, R. W. (2020). *The Impact of COVID-19 on Small Business Owners: The First Three Months after Social-Distancing Restrictions* (No. w27462). National Bureau of Economic Research. https://doi.org/10.3386/w27462

Fujita, S. & Moscarini, G. (2017), "Recall and Unemployment", *American Economic Review* 102(7): 3875-3916.

Gentilini, U., Almenfi, M., Orton, I., & Dale, P. (2020). Social Protection and Jobs Responses to COVID-19 : A Real-Time Review of Country Measures. World Bank, Washington, DC. © World Bank. https://openknowledge.worldbank.org/handle/10986/33635 License: CC BY 3.0 IGO."

Gottlieb, C., Grobovsek, J., & Poschke, M. (2020). Working from Home across Countries. In *Cahiers de recherche* (No. 07–2020; Cahiers de Recherche). Centre interuniversitaire de recherche en économie quantitative, CIREQ. https://ideas.repec.org/p/mtl/montec/07-2020.html

Guan, D., Wang, D., Hallegatte, S., Davis, S. J., Huo, J., Li, S., Bai, Y., Lei, T., Xue, Q., Coffman, D., Cheng, D., Chen, P., Liang, X., Xu, B., Lu, X., Wang, S., Hubacek, K., & Gong, P. (2020). Global supply-chain effects of COVID-19 control measures. *Nature Human Behaviour*, 4(6), 577–587. https://doi.org/10.1038/s41562-020-0896-8

Gulyas, A., & Pytka, K. (2020). Understanding the Sources of Earnings Losses After Job Displacement: A Machine-Learning Approach. In *CRC TR 224 Discussion Paper Series* (crctr224_2020_131v2; CRC TR 224 Discussion Paper Series). University of Bonn and

University of Mannheim, Germany. https://ideas.repec.org/p/bon/boncrc/crctr224_2020_131v2.html

Guven, C., Sotirakopoulos, P., & Ulker, A. (2020). Short-term Labour Market Effects of COVID-19 and the Associated National Lockdown in Australia: Evidence from Longitudinal Labour Force Survey. In *GLO Discussion Paper Series* (No. 635; GLO Discussion Paper Series). Global Labor Organization (GLO). https://ideas.repec.org/p/zbw/glodps/635.html

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., & Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). Nature Human Behaviour, 5(4), 529–538. https://doi.org/10.1038/s41562-021-01079-8.

Hatayama, M., Viollaz, M., and Winkler, H. (2020). "Jobs' amenability to working from home: Evidence from skills surveys for 53 countries." COVID Economics, 211.

Hensvik, L., Le Barbanchon, T., & Rathelot, R. (2020). *Job Search during the COVID-19 Crisis* (SSRN Scholarly Paper ID 3598126). Social Science Research Network. https://doi.org/10.2139/ssrn.3598126

ILO. (2021). ILO Monitor: COVID-19 and the world of work. 7th edition. https://www.ilo.org/wcmsp5/groups/public/---dgreports/--comm/documents/briefingnote/wcms_767028.pdf

Inoue, H., & Todo, Y. (2020). The propagation of economic impacts through supply chains: The case of a mega-city lockdown to prevent the spread of COVID-19. *PLOS ONE*, *15*(9), e0239251. https://doi.org/10.1371/journal.pone.0239251

Juranek, S., Paetzold, J., Winner, H., & Zoutman, F. T. (2020). Labor Market Effects of COVID-19 in Sweden and its Neighbors: Evidence from Novel Administrative Data. In *Discussion Papers* (No. 2020/8; Discussion Papers). Norwegian School of Economics, Department of Business and Management Science. https://ideas.repec.org/p/hhs/nhhfms/2020_008.html

Khamis, M., Prinz, Newhouse, D., Palacios-Lopez, A., Pape, U., &Weber, M. (2021). "The Early Labor Market Impacts of COVID-19 in Developing Countries: Evidence from High-Frequency Phone Surveys." Policy Research Working Paper No. 9510. World Bank, Washington, DC.

Kibrom A., Tafere, Kibrom, T. & Andinet, W. (2020). Winners and Losers from COVID-19 : Global Evidence from Google Search. Policy Research Working Paper; No. 9268. World Bank, Washington, DC. © World Bank. https://openknowledge.worldbank.org/handle/10986/33852 License: CC BY 3.0 IGO.

Kraus, S., Clauss, T., Breier, M., Gast, J., Zardini, A., & Tiberius, V. (2020). The economics of COVID-19: Initial empirical evidence on how family firms in five European countries cope with the corona crisis. *International Journal of Entrepreneurial Behavior & Research*, *26*(5), 1067–1092. https://doi.org/10.1108/IJEBR-04-2020-0214

"Kugler, M., Viollaz, M., Duque,D., Gaddis, I., Newhouse,D., Palacios-Lopez, A., and Weber, M. (2021). How Did the COVID-19 Crisis Affect Different Types of Workers in the Developing World? Jobs Working Paper;No. 60. World Bank, Washington, DC. © World Bank. https://openknowledge.worldbank.org/handle/10986/35950

Lee, S. Y. (Tim), Park, M., & Shin, Y. (2021). *Hit Harder, Recover Slower? Unequal Employment Effects of the COVID-19 Shock* (No. w28354; p. w28354). National Bureau of Economic Research. https://doi.org/10.3386/w28354

Lee, Sang Yoon (Tim), Minsung Park and Yongseok Shin. 2021. "Hit Harder, Recover Slower? Unequal Employment Effects of the COVID-19 Shock." NBER Working Paper No. 28354. National Bureau of Economic Research, Cambridge, MA.

Lyttelton, T., Zang, E., and Musick, K. (2020). Gender Differences in Telecommuting and Implications for Inequality at Home and Work. Available at SSRN 3645561.

Mazzi, C. T., Ndubuisi, G., & Avenyo, E. (2020). *Exporters and global value chain participation: Firm-level evidence from South Africa* (WIDER Working Paper Series wp-2020-145). World Institute for Development Economic Research (UNU-WIDER). https://econpapers.repec.org/paper/unuwpaper/wp-2020-145.htm

McKibbin, W. J., & Fernando, R. (2020). *The Global Macroeconomic Impacts of COVID-19: Seven Scenarios* (SSRN Scholarly Paper ID 3547729). Social Science Research Network. https://doi.org/10.2139/ssrn.3547729

Mongey, S., Pilossoph, L., & Weinberg, A. (2020). *Which Workers Bear the Burden of Social Distancing?* (No. w27085). National Bureau of Economic Research. https://doi.org/10.3386/w27085

Montenovo, L., Jiang, X., Lozano-Rojas, F., Schmutte, I. M., Simon, K. I., Weinberg, B. A., & Wing, C. (2020). *Determinants of Disparities in COVID-19 Job Losses* (SSRN Scholarly Paper ID 3597864). Social Science Research Network. https://papers.ssrn.com/abstract=3597864

Navarro, S. (2010). « Control Functions." *Microeconometrics. The New Palgrave Economics Collection*. https://link.springer.com/chapter/10.1057 percent2F9780230280816_4

Newey, W., Powell, J. & Vella, F. (1999). Nonparametric Estimation of Triangular Simultaneous Equations Models. *Econometrica*, 67, 565–603.

OAMDI. (2021). Jordan - COVID-19 MENA Monitor Household Survey (CMMHH), http://www.erfdataportal.com/index.php/catalog. Version 2.0 of the licensed data files; CMMHH Feb-2021. Egypt: Economic Research Forum (ERF).

Palacios-Lopez, A., Newhouse, D., Pape, U., Khamis, M., Weber, M. & Daniel, P. (2021). The Early Labor Market Impacts of COVID-19 in Developing Countries : Evidence from High-Frequency Phone Surveys. Policy Research Working Paper Series 9510, The World Bank.

Pouliakas, K., & Branka, J. (2020). *EU Jobs at Highest Risk of COVID-19 Social Distancing: Will the Pandemic Exacerbate Labour Market Divide?* (SSRN Scholarly Paper ID 3608530). Social Science Research Network. https://papers.ssrn.com/abstract=3608530

Rio-Chanona, R. M. del, Mealy, P., Pichler, A., Lafond, F., & Farmer, J. D. (2020). Supply and demand shocks in the COVID-19 pandemic: An industry and occupation perspective. *Oxford Review of Economic Policy*, *36*(Supplement_1), 94–137.

World Bank. (2019). Georgia - Beyond Arrivals: Emerging Opportunities for Georgian Firms in Tourism Value Chains (English). Washington, D.C.: World Bank Group. https://openknowledge.worldbank.org/handle/10986/33166

World Bank, (2020a). Jordan Economic Monitor – Fall 2020 : Navigating through Continued Turbulence (English). Washington, D.C. : World Bank Group. http://documents.worldbank.org/curated/en/411101615477814784/Jordan-Economic-Monitor-Fall-2020-Navigating-through-Continued-Turbulence

World Bank. (2020b). Jordan Economic Monitor – Spring 2020 : Weathering the Storm (English). Washington, D.C. : World Bank Group.

http://documents.worldbank.org/curated/en/895901594653936142/Jordan-Economic-Monitor-Spring-2020-Weathering-the-Storm

World Bank. (2020c). Poverty and Welfare Impacts of COVID-19 and Mitigation Policies in Georgia (English). Washington, D.C. : World Bank Group. http://documents.worldbank.org/curated/en/456501608095974011/Poverty-and-Welfare-Impacts-of-COVID-19-and-Mitigation-Policies-in-Georgia

World Bank. (2021a). Country Gender Assessment: Georgia. World Bank, Washington, DC. © World Bank.

https://openknowledge.worldbank.org/handle/10986/35366 License: CC BY 3.0 IGO."

World Bank. (2021b). "Early Labor Market Impacts of COVID-19 in Developing Countries." https://openknowledge.worldbank.org/handle/10986/35047.

World Bank. (2021c). Jordan Economic Update April 2021. Washington, D.C.: World Bank Group. https://www.worldbank.org/en/country/jordan/publication/economic-update-april-2021

Appendix 1: Construction of Variables and Data Summaries

Appendix Table 1:Construction of Variables

Labor Supply Variables		
Variable	Definition	Data sources
Essentialness	Whether workers are in essential businesses or industries (0-1 binomial). The sector categories are mapped from NACE from ISIC	Essential sector list in Italy
Level of adjustment to remote work	Percent of firm workers working remotely	COVID Follow up ES
Infection risk to workers	The extent to which workers in given occupation face infection risks. Total of the three scores: Exposure to disease and infection: How often does this job require exposure to hazardous conditions? Contact with others: How much does this job require the worker to be in contact with others in order to perform it? Physical proximity: To what extent does this job require the worker to perform tasks in close physical proximity to others?	O*NET
Firm closure due to lockdown measures	Number of weeks the firm has been closed due to COVID outbreak	COVID Follow up ES
WFH Index	Physical & Manual index Face-to-face index Low ICT at work index Low ICT at home index (multiplied by -1)	LMPS
Physically demanding and manual task index	Share of physical & manual tasks by individuals: Are you exposed to bending for a long time? Does your job require physical fitness? Is the individual engaged in a craft-related job?	LMPS
In-person face-to-face task index	Share of face-to-face task: Does your job require supervising others?	LMPS
ICT task index	Share of ICT tasks at work: Do you use a computer in your work? If so, is this computer connected to the internet?	LMPS
No internet at home and individual level	Degree of internet access Do you have access to internet at home? Does your family have internet connection? Does your family own a wireless internet router? Do you use the internet on your phone?	LMPS
Labor Demand Variables		
Variable	Definition	Data Sources
Firm closure due to lockdown measures	Number of weeks the firm has been closed due to COVID outbreak	COVID Follow up ES
Firm sales change	Percent change in sales compared to the same month last year	COVID Follow up ES
Adjustments made to technology or products	Whether started or increased business activity online?	COVID Follow up ES

	Whether started or increased delivery or carryout of goods/services?	
Liquidity and solvency of the firm	Whether firm has experienced financing issues (incl. Reduced cashflow, delayed payment, and bankruptcy)	COVID Follow up ES
Policy supports reported	Whether firm has received wage subsidies Whether firm has received other forms of policy support (e.g., deferral of credit payments, rollover of debt, etc.)	COVID Follow up ES
Policy or contractual constraints to workforce reduction	Percentage of firms' workers on permanent contracts in December 2019	COVID Follow up ES
Firm's supply constraints	Whether the firm's supply of inputs, raw materials, or finished goods and materials purchased to resell has decreased	COVID Follow up ES
Global demand shocks	Year-on-year percent change in US and EU total imports from the world (2019 Jun vs. 2020 Jun) Year-on-year percent change in international flights in Jordan (2019 Jun vs. 2020 Jun)	UN Comtrade Flight Radar24
Construction of Instrumental Variables		
Variable	Definition	Data Sources
Percentage of permanent full-time workers with university degree	Whether adopted new technology/business modality Percentage of employees working remotely	2019 ES
Percentage of private ownership Percentage of foreign ownership	Whether had financing issues Whether adopted new technology/business modality	2019 ES
Sales in 2018	Whether adopted new technology/business modality	2019 ES
Firm size	Whether had financing issues Whether adopted new technology/business modality	2019 ES
Whether invested in R&D or externally provided technology	Whether adopted new technology/business modality	2019 ES
Top manager's years of experience in the sector	Whether adopted new technology/business modality	2019 ES
Firm's age	Whether adopted new technology/business modality	2019 ES
Global demand shocks (yoy change in US and EU imports)	Sales, Change in export share of sales	UN Comtrade Flight Radar24
Percentage of working capital borrowed from banks in 2018	Whether had financing issues	2019 ES
Whether had a line of credit and overdraft facility in 2018	Whether had financing issues	2019 ES

Appendix Table 2 Definition of PFPS workers in each dataset

Definition of PFPS workers in each dataset *	Sector	Formality	Permanency
Enterprise Surveys	Private sector	Formal (defined by the survey)	Fulltime permanent
LMPS 2016 (Jordan)	Private sector employee	Formal (defined by the survey)	Permanent workers or fulltime regular workers
CMMHHS 2021 (Jordan) 1/	Private sector employee	Have social insurance	Regular workers
LFS 2019 (Georgia)	Private sector employee	Formal (defined by the survey)	Permanent workers
HFPS (Georgia)	Private sector employee	N/A	N/A

* Constrained by variable availability, PFPS workers are defined slightly different in different surveys. 1/ The questions on social insurance and regularity were only asked pre-COVID in CMMHHS. As long as the post-COVID employment status is still wage workers for private sector, it is assumed that the insurance status and regularity had not changed.

Appendix Table 3: Jordan: Employment Status in 2021 of Workers in PFPS Jobs, Core Productive Sectors

	Employed, pfps core 2021	Employed, other private sector 2021	Unemployed, 2021	Out of labor force, 2021
By gender				
Female	82.7	0.0	14.2	3.1
Male	75.2	2.8	19.2	2.8
By age group				
below 25	76.9	0.0	17.6	5.5
25-45	79.4	3.2	16.2	1.2
above 45	61.7	0.0	30.1	8.2
By education				
Less than basic	66.1	0.0	33.9	0.0
Basic Education	70.1	0.0	27.8	2.0
Secondary Education	79.8	17.0	15.8	4.3
Higher Education	80.6	4.0	12.2	3.2
By nationality				
Jordanian	78.8	2.7	15.1	3.4
Syrian	93.2	0.0	6.8	0.0
Palestinian	59.5	0.0	40.5	0.0
Total	76.7	2.3	18.2	2.8

Source: CMMHH 2021.
Note: Denominator: PFPS in core productive sector in 2020 within each group

Appendix Table 4 Jordan: Demographic Structure, Formal Private Sector Permanent Workers (PFPS)

	2020 share of employed (working age, 18-64)	2020 share of employed (all age)	2016 share of employed (working age, 18-64)	2016 share of employed (working age, 18-64, excl. other nationality)
By gender				
Male	74.5	80.2	80.2	76.7
Female	25.5	19.8	19.9	23.3
By education				
1. Less than basic	7.4	17.5	17.3	10.7
2. Basic	21.7	23.3	23.3	25.8
3. Secondary	13.9	14.4	14.5	15.2
4. Higher education	57.0	44.9	45.0	48.4
By nationality				
1. Jordanian	88.5	75.6	75.5	93.9
2. Palestinian	9.8	2.8	2.8	3.5
3. Syrian	1.7	2.2	2.2	2.7
4. Other	-	19.5	19.5	-
By age				
below 25	17.0	15.2	14.9	15.8
25 to 45	71.8	69.8	70.3	68.7
above 45	11.2	15.0	14.8	15.5

Source: CMMHH 2021 and LMPS 2016.

Appendix Table 5: Jordan: Pre-COVID Share of Private Sector Wage Earners in Non-permanent Jobs by Demographic Group, 2016 and 2020

	2020 CMMHH (working age excl. other nationalities)	2016 LMPS (working age excl. other nationalities)
By Gender		
Female	40.7	32.5
Male	61.6	55.5
By age group		
below 25	66.0	59.6
25-45	54.8	48.6
above 45	60.3	54.3
By education		
Less than basic	80.7	77.5
Basic Education	68.7	58.6
Secondary Education	62.0	52.4
Higher Education	38.6	25.7
By nationality		
Jordanian	53.9	42.6
Syrian	93.3	91.1
Palestinian	48.9	73.6
Total	57.8	51.6

Sources: CMMHH Jordan 2021 and LMPS 2016.

Appendix Table 6 Jordan: Pre-COVID Share of PFPS Workers by Demographic Group, 2016 and 2020

	2020 CMMHH (working age excl. other nationalities)	2016 LMPS (working age excl. other nationalities)
By Gender		
Female	59.3	67.5
Male	38.4	44.5
By age group		
below 25	34.0	40.4
25-45	45.2	51.4
above 45	39.7	45.7
By education		
Less than basic	19.3	22.5
Basic Education	31.3	41.4
Secondary Education	38.0	47.6
Higher Education	61.4	74.3
By nationality		
Jordanian	46.1	57.4
Syrian	6.7	8.9
Palestinian	51.1	26.4
Total	42.2	48.4

Sources: CMMHH Jordan 2021 and LMPS 2016.

Appendix Table 7 Jordan: Modeled Production versus Non-Production Worker Job Losses, Wave 1 (with firm closure)

	Model Projections		
By sector	Production workers	Non-production workers	All workers
1. Chemicals	5.2	4.5	4.9
2. Food, drink, and tobacco	7.7	9.3	8.1
3. Garments	19.6	14.1	18.7
4. Hotel, restaurant, and transportation	19.4	12.2	17.8
5. Machinery, electronics, and construction	21.6	-1.7	16.3
6. Metals and non-metallic minerals	7.8	7.2	7.6
7. Wholesale, retail, and other services	21.2	12.7	19.3
8. Wood, paper, publishing, and printing	24.9	-1.7	16.7
Total	18.0	9.0	15.8

Sources: LMPS (2016), World Bank Enterprise Surveys, and authors' calculations.
A positive figure indicates jobs lost. Model-predicted estimates are based on projected jobs lost using a multi-stage model and the employment structure in LMPS. Survey-measured jobs lost are based on directly computed sector-average job losses. In both cases, to estimate the allocation of jobs lost to production and non-production workers, we use the 2013 and 2019 World Bank Enterprise Surveys for Jordan and estimate sector-specific Tobit polynomial models. The calibrated models are applied to estimate the numbers of production and non-production workers of the pre-COVID baseline and the COVID wave. Survey weights applied in all calculations.

Appendix Table 8 Georgia: Projected Production versus Non-Production Job Losses, Wave 1 (with firm closure)

	Econometric Model Projections			Survey- measured
By sector	Production workers	Non-Production workers	Total Jobs Lost	Total Jobs Lost
1. Chemicals	11.6	-38.7	6.0	30.3
2. Food, drink, and tobacco	12.6	-0.9	7.7	13.2
3. Garments	32.1	36.3	33.4	44.4
4. Hotel, restaurant, and transportation	29.9	14.4	27.4	39.9
5. Machinery, electronics, and construction	28.6	16.3	23.9	18.9
6. Metals and non-metallic minerals	12.5	-1.2	8.4	5.2
7. Wholesale, retail, and other services	18.9	-3.4	15.0	8.2
8. Wood, paper, publishing, and printing	31.5	18.3	26.8	17.5
Total	22.7	8.0	19.0	16.8

Sources: LFS 2019, World Bank Enterprise Surveys, and authors' calculations.
Note: Econometric Model Projections are based on projected jobs lost using a multi-stage model and the employment structure in LFS. A positive figure indicates jobs lost. Survey weights applied in all calculations. To estimate the allocation of jobs lost to production and non-production workers, we use the 2013 and 2019 World Bank Enterprise Surveys for Georgia and estimate sector-specific Tobit polynomial models. The calibrated models are applied to estimate the numbers of production and non-production workers of the pre-COVID baseline and the COVID wave. Survey-measured jobs lost are based on sector-average job losses from CFUWBES 1 directly and rescaled to match modeled mean (including the selection correction applied).

Appendix Table 9: Jordan: All Labor Market Impacts Due to COVID-19, Percentage of Formal Private Sector Permanent Employees in Core Productive Sectors by Group as of February 2020 Experiencing the following in the Previous 60 Days

	Temp. layoff/suspension (without pay)	Permanent layoff/ suspension	Reduced hours	Reduced pay	Delay in wage
By gender					
Male	6.2	16.1	13.5	8.9	15.8
Female	4.5	18.8	4.1	4.8	30.0
By education					
1. Less than basic	0.0	33.9	0.0	7.5	46.7
2. Basic	3.9	27.8	3.7	0.0	14.9
3. Secondary	12.4	16.0	13.0	8.1	12.4
4. Higher education	5.4	9.2	16.4	11.5	17.5
By nationality					
1. Jordanian	6.8	18.3	13.6	8.6	21.5
2. Palestinian	0.0	8.1	0.0	0.0	3.4
3. Syrian	3.5	6.8	3.5	30.2	3.5
By age					
below 25	11.3	11.1	13.1	3.8	27.0
25 to 45	4.3	14.1	11.6	9.6	16.9
above 45	7.1	37.4	9.7	5.1	18.0
By personal net monthly wage in 2020					
Q1	15.8	9.7	12.1	5.9	38.0
Q2	10.6	26.7	11.4	5.0	18.4
Q3	0.0	35.7	21.4	14.1	25.1
Q4	3.0	17.1	7.9	11.4	10.8
Q5	4.2	8.3	10.8	7.6	14.6
By sector					
Manufacturing	10.8	29.7	7.4	4.5	9.8
Construction or utilities	0.0	0.0	33.2	0.0	56.2
Retail or Wholesale	3.1	14.7	11.0	12.6	18.9
Transportation and storage	8.2	16.2	23.8	15.5	20.0
Accommodation and food services	3.6	19.0	5.0	7.9	26.0
Information and communication	10.4	3.5	18.8	7.5	7.5
Financial activities or real estate	-	-	-	-	-

Education	-	-	-	-	-
Health	-	-	-	-	-
Other services	3.8	15.1.	0.0	0.0	0.0
Total	5.8	16.7	14.1	10.9	18.7

Source : CMMHH, Jordan (Jan.-Mar. 2021).

Appendix Table 10: Share of PFPS Workers Working from Home by Demographic Characteristic, Jordan

Demographic Breakdown	Percentage of Demographic Group
By gender	
Male	17.2
Female	59.0
By education	
1. Less than basic	0.0
2. Basic	1.8
3. Secondary	6.1
4. Higher education	46.7
By nationality	
1. Jordanian	28.8
2. Palestinian	23.4
3. Syrian	4.4
By age	
below 25	21.6
25 to 45	32.3
above 45	9.3
By personal net monthly wage quintile in 2020	
Q1	15.1
Q2	21.2
Q3	25.6
Q4	33.3
Q5	37.2
By sector	
Manufacturing	6.4
Construction or utilities	17.1
Retail or Wholesale	12.6
Transportation and storage	0.0
Accommodation and food services	14.4

Information and communication	70.1
Financial activities or real estate	42.0
Education	83.2
Health	18.1
Other services	28.4
Total	27.9

Source: CMMHH, Jordan (Jan.- Mar. 2021)
*Sample includes private permanent formal employees pre COVID. Permanent workers are defined using regular workers; formal is defined as workers who have social insurance.
Individual weights applied in calculations.

Appendix Table 11 Jordan: Employment Status Shift from 2020 to 2021 for PFPS Workers in Core Productive Sectors by Demographic Group

Percentage of all employed in 2020 in each demographic segment, working age, formal private sector permanent employment)					
	Employed formal private sector in 2021	Employed elsewhere in 2021	Unemployed in 2021	Out of labor force in 2021	Percentage of Jobs Lost
By gender					
Male	75.2	2.8	19.2	2.8	24.8 percent
Female	82.7	0.0	14.2	3.1	17.3 percent
By education					
1. Less than basic	66.1	0.0	33.9	0.0	33.9 percent
2. Basic	70.1	0.0	27.8	2.0	29.9 percent
3. Secondary	78.6	1.2	15.8	4.3	21.4 percent
4. Higher education	80.6	4.0	12.2	3.2	19.4 percent
By nationality					
1. Jordanian	78.8	2.7	15.1	3.4	21.2 percent
2. Palestinian	59.5	0.0	40.5	0.0	40.5 percent
3. Syrian	93.2	0.0	6.8	0.0	6.8 percent
By age					
below 25	76.9	0.0	17.6	5.5	23.1 percent
25 to 45	79.4	3.2	16.2	1.2	20.6 percent
above 45	61.7	0.0	30.1	8.2	38.3 percent
Total	76.7	2.3	18.2	2.8	23.3 percent

Source: CMMHH, Jordan (Jan.- Mar. 2021)

Appendix 2: Econometric Results Tables

Appendix Table 12: Stage1. Selection Model to Correct for Exclusion Bias Due to Non-Response, Jordan

Dependent variable: D=1 if none of the important variables is missing	Probit (incl. in regression sample = 1, unweighted)
Interviewee was the same person as in baseline survey (=1 if true)	0.716***
	(0.185)
Firm size, categorical = 2, medium	0.409***
	(0.139)
Firm size, categorical = 3, large	0.0632
	(0.197)
Top manager's years of experience in the sector (years)	0.0164***
	(0.00632)
Constant	-0.545***
	(0.205)
Observations	541
Standard errors in parentheses	
*** p<0.01, ** p<0.05, * p<0.1	

Appendix Table 13: Adoption or Increased Use of Digital/Other Delivery Means, Jordan

Dependent variable: whether started or increased online or delivery business activities (1=yes)	Weighted Probit: Selected	Weighted Probit: Including Full Set of Exogenous Regressors
percentage of foreign ownership	0.0136**	0.0163**
	(0.00616)	(0.00659)
temporarily closed due to COVID (weeks of closure)		-0.0238
		(0.0241)
total score of infection risk (higher = more risk)		0.00440
		(0.00706)
whether supply of goods, materials, and inputs decreased (1=yes)		-0.364
		(0.342)
change in export share of sales (percentage difference)		-0.000317
		(0.00712)
whether supplies of goods and materials decreased (1=yes) # change in export share		0.00152
		(0.00846)
whether the firm had export sales in 2018 (1=yes) # global demand shock		0.00273
		(0.00429)

Constant	0.109	-0.168
	(0.100)	(1.169)
Observations	485	382
Robust standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		

Appendix Table 14: Adoption or Increased Use of Digital/Other Delivery Means, Georgia (Results not used in Later Stage Regressions)

Dependent variable: whether started or increased online or delivery business activities (1=yes)	Coefficients
firm size, categorical = 2, 2. medium	-0.0322
	(0.214)
firm size, categorical = 3, 3. large	-0.314
	(0.289)
percentage of foreign ownership	0.00577
	(0.00385)
top manager's years of experience in the sector (years)	-0.0114
	(0.00944)
temporarily closed due to COVID (weeks of closure)	-0.0244
	(0.0217)
whether supply of goods and materials has decreased (1=yes)	0.384*
	(0.213)
whether the firm had export sales in 2018 (1=yes) # global demand shock (yoy change)	0.0163*** (0.00519)
Constant	-0.211
	(0.246)
Observations	441

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 15: Determinants of Financial Difficulties (first stage), Jordan

Dependent variable: whether faced financial issues (reduced cash, delayed payment, and solvency) (1=yes)	Weighted Probit
Percentage of working capital borrowed from banks in 2018	-0.0129*
	(0.00715)
Whether the firm has a line of credit and overdraft facility in 2018 (1=yes)	-0.133
	(0.470)
Top manager's years of experience in the sector (years)	-0.00507
	(0.0187)
Constant	2.046***
	(0.444)
Observations	360

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 16: Determinants of Financial Difficulties (first stage), Georgia

Dependent variable: whether faced financial issues (reduced cash, delayed payment, and solvency) (1=yes)	Includes firm size dummies	Specification used
Firm size, categorical = 2, 2. medium	-0.670*	
	-0.392	
Firm size, categorical = 3, 3. large	-0.484	
	(0.306)	
Percentage of working capital borrowed from banks in 2018	0.00279	0.00296
	(0.00517)	(0.00512)
whether the firm has a line of credit and overdraft facility in 2018 (1=yes)	0.704**	0.662*
	(0.354)	(0.379)
top manager's years of experience in the sector (years)	0.000284	
	(0.0144)	
Percentage of foreign ownership	0.0117***	0.0103**
	(0.00393)	-0.004
Constant	0.955***	0.774***
	(0.313)	(0.187)
Observations	558	563

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 17: Determinants of Percentage of Employees Working from Home, Jordan and Georgia

Dependent variable: share of workforce working remotely	Jordan	Georgia
Percentage of permanent full-time workers with university degree	0.0901*	0.0101
	(0.0527)	(0.0205)
Firm size, categorical = 2, medium	3.566	7.174***
	(3.106)	(3.695)
Firm size, categorical = 3, large	9.264*	11.44***
	(4.856)	(3.799)
Essential industry		1.376
		(1.748)
Physically demanding and manual task index (higher = more intense)	1.636	-1.309
	(1.149)	(2.492)
In-person face-to-face task index (higher = more risk)	-2.483	-1.908
	(2.202)	(3.819)
ICT task index (higher = more ict use)	-4.999*	-6.503*
	(2.674)	(3.360)
Internet at home at individual level (higher = having internet access)	-0.753	
	(3.979)	
Constant	3.753*	-0.396
	(2.274)	(1.633)
Observations	436	535
Adjusted R-squared	0.145	0.042
F-test(all components of *wfh*)	1.548	1.266
Prob>F	0.187	0.285

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table 18 Georgia: Alternative Sales Equation Specifications

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
temporarily closed due to COVID (weeks of closure)	-4.060***	-4.070***	-4.102***	-4.096***	-3.974***	-3.903***	-3.893***	-3.991***	-3.995***	-3.991***
	(0.608)	(0.613)	(0.602)	(0.606)	(0.599)	(0.572)	(0.570)	(0.576)	(0.580)	(0.576)
Infection risk (private)	-0.252	-0.267*	-0.272*	-0.257*	-0.236	-0.241*	-0.225	-0.227	-0.248*	-0.227
	(0.154)	(0.151)	(0.151)	(0.149)	(0.154)	(0.144)	(0.146)	(0.146)	(0.142)	(0.146)
whether supply of goods and materials has decreased (1=yes)	-18.91***	-19.32***	-19.85***	-19.96***	-19.90***	-18.83***	-18.74***	-18.02***	-18.29***	-18.02***
	(5.785)	(5.726)	(5.661)	(5.621)	(5.665)	(5.692)	(5.694)	(5.666)	(5.640)	(5.666)
change in export share of sales (percentage difference)	-0.217	-0.216		-0.0539	-0.218					
	(0.344)	(0.339)		(0.171)	(0.341)					
whether supplies of goods and materials decreased (1=yes) # change in export sha	0.254	0.249	0.0559		0.242					
	(0.332)	(0.326)	(0.0999)		(0.327)					
whether the firm had export sales in 2018 (1=yes) # global demand shock (yoy cha	0.318**	0.308**	0.271**	0.322**	0.275**	0.259***	0.260***	0.307***	0.294***	0.307***
	(0.129)	(0.128)	(0.105)	(0.134)	(0.125)	(0.0729)	(0.0730)	(0.0808)	(0.0796)	(0.0808)
percentage of foreign ownership	0.184*				0.150		0.104	0.159		0.159
	(0.110)				(0.111)		(0.0947)	(0.0991)		(0.0991)
whether started or increased business activity online (1=yes)	-12.25	-8.654	-8.681	-8.483				-13.85	-10.67	-13.85
	(8.434)	(8.425)	(8.369)	(8.365)				(8.484)	(8.435)	(8.484)
residuals from adaption probit equation	17.29**	14.58*	14.35*	14.64*	8.620			16.39**	13.90*	16.39**
	(7.808)	(7.654)	(7.620)	(7.618)	(5.389)			(7.792)	(7.625)	(7.792)
Constant	31.28	34.12	35.58	33.14	25.55	25.69	22.38	26.38	30.00	26.38
	(24.87)	(24.41)	(24.33)	(24.20)	(25.19)	(22.94)	(23.60)	(23.38)	(22.82)	(23.38)
Observations	366	366	366	366	366	413	413	406	406	406
Adjusted R-squared	0.418	0.407	0.406	0.407	0.412	0.388	0.391	0.406	0.399	0.406

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table 19 Jordan: Sectoral Polynomial Models of the Relationship Between Production and Non-production Workers

Dependent variable: Number of non-production workers	1. Chemicals	2. Food, drink, and tobacco	3. Garments	4. Machinery electronics and construction	5. Metals and non-metallic minerals	6. Plastic and rubber	7. Wholesale, retail, hotel, restaurant	8. Wood, paper, publishing, and printing
Number of production workers	0.937***	0.468***	-0.164	-0.0311	0.495***	0.234***		-0.282
	(0.215)	(0.0635)	(0.110)	(0.117)	(0.152)	(0.0339)		(0.340)
Number of production workers ^ 2	-0.00326**	-0.00114***	0.000957***	0.00392**	-0.00432***			0.0225*
	(0.00125)	(0.000203)	(0.000263)	(0.00167)	(0.00141)			(0.0127)
Number of production workers ^ 3	4.22e-06***	9.01e-07***	-7.71e-07***	-1.67e-05**	1.83e-05***			-0.000293*
	(1.56e-06)	(1.50e-07)	(1.95e-07)	(7.20e-06)	(4.16e-06)			(0.000158)
Number of production workers ^ 4			1.71e-10***	1.86e-08**	-2.10e-08***			1.11e-06*
			(0)	(8.67e-09)	(3.80e-09)			(5.93e-07)
Year = 2019	-12.28	1.737	5.372	1.653	-3.716	-0.134		4.746**
	(8.245)	(3.192)	(8.639)	(1.885)	(3.252)	(1.749)		(1.996)
Constant	-0.544	-0.130	7.517	3.066*	0.648	1.502		2.115
	(7.710)	(2.812)	(7.823)	(1.648)	(3.207)	(1.581)		(2.284)
Observations	67	156	132	46	69	25		36

Note: The data on production and non-production workers are sourced from the 2013 and 2019 World Bank Enterprise Survey. A year dummy (2019 = 1) is added to broadly capture the technological change.

Appendix Table 20 Georgia: Sectoral Polynomial Models of the Relationship Between Production and Non-production Workers

Dependent variable: Number of non-production workers	1. All manufacturing	2. All services (small/med firms)	3. All services (med/large firms)
Number of production workers	0.720***	5.029	0.261***
	(0.0922)	(2.138)	(0.0279)
Number of production workers ^ 2	-0.00216***	-0.553*	
	(0.000389)	(0.231)	
Number of production workers ^ 3	1.65e-06***	0.0205*	
	(3.14e-07)	(0.00862)	
Number of production workers ^ 4		-0.000193*	
		(8.19e-05)	
Year = 2019	7.327*		-6.456
	(4.060)		(5.880)
Constant	-7.896**	-11.71	1.878
	(3.825)	(5.883)	(1.455)
Observations	295	7	55

Note: The data on production and non-production workers are sourced from the 2013 and 2019 World Bank Enterprise Survey. A year dummy (2019 = 1) is added to broadly capture the technological change. Given the large percentage of missing values on production and non-production workers in Georgia, the sectors are consolidated to better fit the polynomial models. As the service sector only has 7 observations (all in 2013), the model could not reliably predict the non-production workers for some medium or large firms. Therefore, the model from Jordan is used for these firms.

Most Recent Jobs Working Papers:

63. Migrants, Markets and Mayors Rising above the Employment Challenge in Africa's Secondary Cities – Key Insights. (2021)
    Christiaensen, Luc and Lozano Gracia, Nancy.

62. What was the Impact of Creating Better Jobs for more People in China's Economic Transformation? What we know and Questions for Further Investigation. (2021)
    Merotto, Dino and Jiang, Hanchen

61. Opportunities for Youth and Women's Participation in Ghana's Labor-Intensive Public Works Program (2021)
    Dadzie, Christabel E. and Ofei-Aboagye, Esther.

60. How Did the Covid-19 Crisis Affect Different Types of Workers in The Developing World? (2021)
    Maurice Kugler, Mariana Viollaz, Daniel Duque, Isis Gaddis, David Newhouse, Amparo Palacios-Lopez and Michael Weber.

59. Determinantes Del Crecimiento De La Demanda Laboral Y De La Productividad Del Sector Privado (Spanish) (2021)
    Mariana Vijil

58. The Early Labor Market Impacts of Covid-19 In Developing Countries: Evidence from High-Frequency Phone Surveys (2021)
    Melanie Khamis, Daniel Prinz, David Newhouse, Amparo Palacios-Lopez, Utz Pape and Michael Weber

57. Empirical Evidence on Firm Growth and Jobs in Developing Countries (2020)
    Johanne Buba, Alvaro Gonzalez and Anam Rizvi

56. Promoting Female Labor Force Participation (2020)
    Svetlana Pimkina and Luciana de La Flor

55. Structural Transformation and Labor Market Performance In Ghana (2020)
    Mpumelelo Nxumalo and Dhushyanth Raju

54. Just Coal Transition in Western Macedonia, Greece-Insights from the Labor Market (2020)
    Luc Christiaensen and Céline Ferré

Click here for full Jobs Paper Series

WORLD BANK GROUP
Jobs

Address: 1776 G St, NW, Washington, DC 20006
Website: http://www.worldbank.org/en/topic/jobsanddevelopment
Twitter: @WBG_Jobs
Blog: https://blogs.worldbank.org/jobs/