Who will Bear the Brunt of Lockdown Policies? Evidence from Tele-workability Measures Across Countries

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Abstract

Lockdowns imposed around the world to contain the spread of the COVID-19 pandemic are having a differential impact on economic activity and jobs owing to differences in the ability to work remotely. This paper presents a new index of the feasibility to work from home to investigate what types of jobs are most at risk for 35 advanced and emerging market economies. Cross-country heterogeneity in the ability to work remotely reflects differential access to and use of technology, sectoral mix, and occupational selection. Workers least likely to work remotely also tend to be young, without a college education, working for non-standard contracts, employed in smaller firms, and those at the bottom of the earnings distribution, suggesting that the pandemic could exacerbate inequality. We estimate that over 97.3 million workers, equivalent to about 15 percent of the workforce, are at high risk of layoffs and furlough from lockdowns across the countries in our sample. Policies should account for demographic and distributional considerations both during the crisis and in its aftermath.

JEL Classification Numbers: D24, J22, J61, O30, R12, R32

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I. Introduction

Social distancing policies implemented to contain the COVID-19 pandemic are affecting a large share of workers across the world. Millions of workers are unemployed and countless jobs are increasingly at risk.[1] Workers in occupations requiring physical presence at the workplace or those jobs that require a high level of personal proximity have limited scope for working from home. Some of these workers commensurately face higher risk of reductions in hours or pay, temporary furloughs, or permanent layoffs. What type of jobs are most at risk? How does the level of "tele-workability" depend on worker characteristics, such as age, educational attainment, gender, employment status, and earnings? How does the feasibility to work remotely vary across advanced and emerging economies? Answers to these questions can inform the social protection and labor market policies needed to support workers both during and after lockdowns and curb rising income inequality.

We construct a new index of "tele-workability" for 35 advanced and emerging market economies using a task-based approach. We use two sources of data to develop a measure of tele-workability: occupation-level classification of feasibility of working from home derived by Dingel and Neiman (2020) for the US and individual-level data from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC). The latter has the advantage of measuring task or skill content at the worker level for a large sample of countries. Our estimation approach relies on an Expectation Maximization algorithm to map occupation-level measures of the feasibility of working at home to individual-level observations in the PIAAC dataset and derive predicted tele-workability scores for each worker. Individual-level scores allow us to conduct a more nuanced analysis of worker characteristics at the task level for a large group of countries. Given that PIAAC surveys are representative at the national level, we are able to capture differences in the ability to telework that are driven by underlying differences in the sectoral mix, demographic composition, and access to technologies necessary for teleworking across countries.

We find that workers least likely to work remotely are concentrated in the sectors hit hardest by the crisis (ILO, 2020): accommodation and food services, transportation, and retail and wholesale sectors. We estimate that over 97.3 million workers, equivalent to about 15 percent of the workforce, are at high risk of layoffs and furlough across the countries in our sample. Vulnerable workers tend to be young, without a college education, in less secure work arrangements (e.g., in part-time employment), and employed in small and medium enterprises (SMEs). Workers at the bottom of the earnings distribution are most at risk of earnings loss, suggesting that the COVID-19 crisis could exacerbate inequality. Cross-country heterogeneity reflects differences in the structure of production (e.g., size of manufacturing versus services sectors), use of technology, and occupational selection, and thus differential distribution of workers across jobs. Workers in emerging market economies are likely to face significant challenges during strict lockdowns given limited access to technology. Interestingly, differences in earnings and ability to work

[1] ILO (2020) and BLS (2020).

remotely are less stark for those at the top and bottom of the earning distribution in emerging market economies compared to some advanced economies.

This paper contributes to the literature examining workers' ability to perform their jobs from home and the labor market consequences. Evidence from the US (Dingel and Neiman, 2020; Mongey, Pilossoph, and Weinberg, 2020; Hensvik, Le Barbanchon, and Rathelot, 2020) and several advanced European countries (Boeri, Caiumi, Paccagnella, 2020; Fadinger and Schymik, 2020; Office of National Statistics, 2020) suggests that about 40 percent of jobs can be performed at home, ranging from 24 percent in Italy to 42 percent in Germany.[2] In developing economies, up to 20 percent of urban population can work from home (Saltiel, 2020; Gottlieb, Grobovsek, and Poschke, 2020); this number is much smaller if rural population is taken into account. These studies use occupation-level data to examine labor market implications of social distancing policies. A drawback of this approach is that it assumes that tasks performed within occupations across countries, sectors, firms, and individuals are identical. Under this assumption, differences in levels of tele-workability across countries only stem from variation in the occupational distribution. However, differences in tele-workability levels within a given occupation across countries can depend on various factors, including access to information and communication technologies (ICT).

In this paper, we go beyond occupational classifications of feasibility of teleworking and leverage information on the specific job-task and socio-economic characteristics of workers, using comparable data for a large set of advanced and emerging economies. Since our estimation approach accounts for heterogeneity of worker tasks in a given occupation, it provides a more granular understanding of how social distancing policies can affect individual workers. It also allows us to relax the assumption implicit in other studies that workers have the same work responsibilities and access to the same technologies within and across countries to perform their tasks.

Our methodology also provides a more realistic picture of the jobs at-risk within a given occupation compared to other cross-country studies. A common approach in the literature that examines cross-country differences in the feasibility to work from home is to apply the index developed by Dingel and Neiman (2020) at the 5-digit SOC level for the US to 1- or 2-digit ISCO occupational level for other countries. This methodology assumes that all narrowly defined occupations within the single-digit occupations have the same level of tele-workability and can substantially over- or under-state the level of tele-workability for a given individual. Our approach accounts for individual-level heterogeneity and thus sidesteps the assumption of equal tele-workability scores within each broadly defined occupation. For instance, compared to

[2] Mongey, Pilossoph, and Weinberg (2020), Boeri, Caiumi, and Paccagnella (2020) and Fadinger and Schymik (2020) rely on occupation-level classifications of the feasibility of working from home similarly to Dingel and Neiman (2020) to derive country-level estimates. An alternative methodology adopted by Hensvik, Le Barbanchon, and Rathelot (2020) and the Office of National Statistics (2020) relies on time-use and population surveys to estimate the share of workers able to work from home and produces similar results.

Gottlieb, Grobovsek, and Poschke (2020) who find that over 70 percent of managers and professionals can work from home, we show that these occupations have a significantly lower level of tele-workability at about 42 percent.

This paper is structured as follows. The next section presents the data and methodology. Section III presents the aggregate index across countries, occupations, and sectors. Section IV examines the role of individual characteristics; Section IV presents analysis of jobs at risk, and Section V concludes.

II. Data and Methodology

We combine two sources of data to develop our measures for tele-workability: occupation-level classification of the feasibility of working from home derived by Dingel and Neiman (2020) for the US and worker-level data for 35 countries from the OECD's Programme for the International Assessment of Adult Competencies (PIAAC).

Dingel and Neiman (2020) use Occupational Information Network (O*NET) survey data from the US to designate whether an occupation can feasibly be performed from home, based on information about "work context" and "generalized work activities." Their index of tele-workability is constructed at the level of 6-digit SOC codes takes on values of 0 (occupation cannot be done at home) or 1 (occupation can be done at home). The survey questions used for this classification capture information such as whether work is done outdoors, whether it requires use specialized or protective equipment, requires physical activity, etc. For instance, if an average respondent in a given occupation reports using email less than once a week or reports that performing for and or working directly with the public is very important, the occupation is deemed as not suitable for teleworking.

Assessing the level of tele-workability at the occupational level, however, has a drawback in that it may be not suitable for comparisons across demographic groups and countries. Under this assumption, differences in the level of tele-workability between two group of individuals (e.g., younger and older workers), can only arise from differential selection into occupations. Consequently, this assumption obscures the differences that can arise from variation in job task composition or access to ICT. Thus, individuals working in the same occupation but living in different countries may have a very different level of tele-workability due to access to a computer or the internet. To address this drawback, we map the occupation level index to the individual level similar to Arntz, Gregory, and Zierahn (2017) and Brussevich, Dabla-Norris and Khalid (2019). Using individual-level data, allows us to account for the fact that individuals within the same occupation often perform different tasks.

To extend the index of tele-workability to a cross-country level, we use the OECD's Programme for the International Assessment of Adult Competencies (PIAAC) database which collects

nationally representative individual-level information for 35 advanced and emerging countries.[3] This survey contains demographic data for workers and information on their occupations and sectors of employment. In addition, the survey captures detailed information on the nature of work activities, such as physical work associated with caregiving and manual labor, flexibility in performing tasks, flexibility in work hours, whether analytical or interpersonal tasks are performed (e.g., writing reports, solving complex problems, and negotiating with people), use of technology or software in the workplace, among others.

In order to combine the two data sources, we map occupational categories from the O*NET data to the PIAAC data. This allows us to relate tele-workability of occupations to job content and worker characteristics. Our methodology also provides crucial insights into which occupations and jobs may be at risk of continued disruption in the post-COVID era due to potential changes in consumer preferences, containment measures and even repeat lockdowns.[4]

Table 1. Task and Skill Variables used in EM Algorithm

Survey Question	Measure (range)
How often do you use Internet to obtain work-related information at work?	Frequency (never – every day)
How often do you use programming language at work?	Frequency (never – every day)
How often do you use a computer for real-time discussions?	Frequency (never – every day)
How often do you use computer for email?	Frequency (never – every day)
How often do you work with spreadsheets?	Frequency (never – every day)
How often does your job require working physically for long?	Frequency (never – every day)
How often do you teach people at work?	Frequency (never – every day)
How often do you save complex problems at work?	Frequency (never – every day)
How often do you make presentations at work?	Frequency (never – every day)
How often do you organize your own time?	Frequency (never – every day)
Can change your work hours?	Levels (not at all – to a very high extent)
Can you choose how to do the work?	Levels (not at all – to a very high extent)
Level of computer use at work	Levels (straightforward - complex)

Source: PIAAC Survey.
Notes: Frequency questionnaire items contain five responses: never, less than once a month, less than once a week but at least once a month, at least once a week but not every day, and every day. Levels of computer use at work include "straightforward," "moderate," and "complex." The rest of the variables are measures on the following scale: "not at all," "very little," "to some extent," "to high extent," and "to very high extent."

[3] We use information from PIAAC surveys were conducted in three rounds between 2011 and 2017.

[4] Our analysis does not explicitly distinguish between "social" jobs which require face-to-face interaction for consumption and "essential" jobs which were not subject to government mandated lockdowns.

PIAAC data contains occupational information at the 2-digit ISCO classification level, which is a higher level of aggregation than the 6-digit SOC codes in O*NET, resulting in one PIAAC occupation being potentially mapped to several measures of tele-workability.[5] We allow individual workers to be mapped to multiple indices of tele-workability, based on the crosswalk between the 6-digit SOC codes and the 2-digit ISCO codes. We then use the iterative Expectation Maximization (EM) algorithm where individual-level data (demographic data and work characteristics) is regressed on associated measures of the tele-workability index, in order to find the model of best fit between worker characteristics and occupation level tele-workability using data for US workers only. Specifically, we estimate an individual-level regression:

$$t_{ij} = \sum_{n=1}^{N} \beta_n X_{in} + \epsilon_{ij},$$

where i denotes individuals, j denotes duplicates of these individuals when multiple probabilities are associated with one individual due to differences in the aggregation level of occupations, t_{ij} is the tele-workability score, and X_{in} contains *N* individual, job, and task characteristics. β_n are parameters which capture the impact of the regressors on the tele-workability index, which takes values of 0 or 1. To run the EM algorithm, we use a set of individual characteristics (gender, education, income deciles, immigration status, and age) and a set of skills used in the workplace summarized in Table 1. We transform all frequencies into continuous measures indicating the number of days a person is engaged in a given activity per week.

We use a weighted Generalized Linear Model (GLM) for our estimation, with equal initial weights for all duplicates j for individual i. For each iteration of the regression, we compare the prediction from our estimated model with the Dingel and Neiman (2020) occupation-level measure and recalculate the weights as per Ibrahim (1990):

$$w_{ij} = \frac{f(\hat{t} - t_{ij}|x_{in}, \beta_n)}{\sum_{n=1}^{N} f(\hat{t} - t_{ij}|x_{in}, \beta_n)},$$

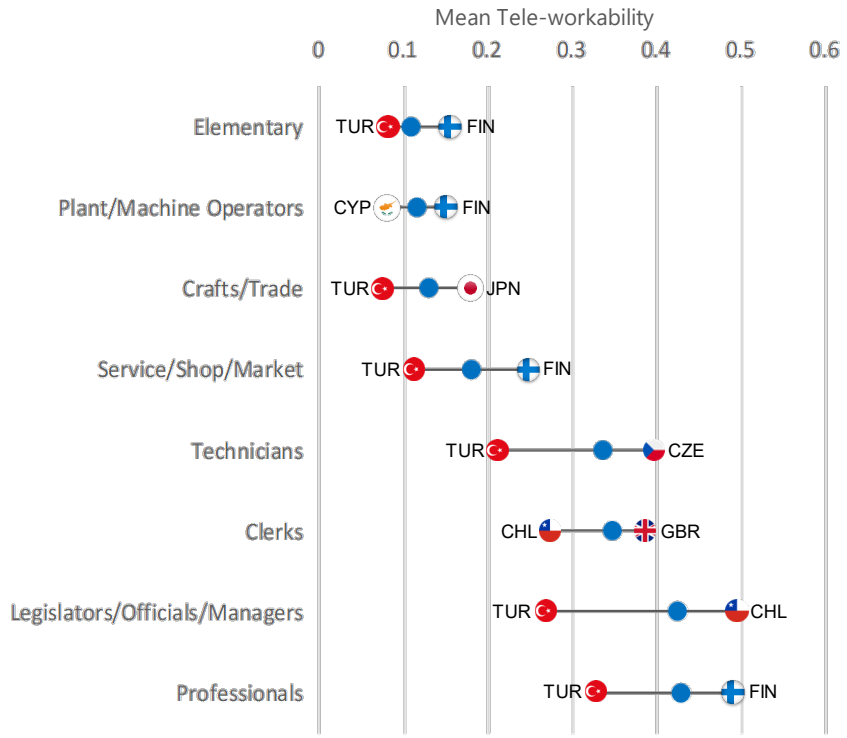
where $f(.)$ is the standard normal density and $\hat{t}$ is the predicted value of tele-workability. Once weights converge and best fit is achieved, the estimated parameters β_n are applied to worker characteristics for all countries in the PIAAC sample, allowing us to estimate the probability of tele-workability across the full sample at the level of individual workers. The tele-workability index takes on values between 0 and 1, with higher numbers indicating greater feasibility of working from home.

[5] We use a crosswalk between 6-digit SOC codes and 4-digit ISCO codes from the US Bureau of Labor Statistics (BLS). Annex 1 provides a correspondence between 2-digit and 4-digit ISCO codes.

III. Cross-Country Evidence: Tele-workability Index, Occupations and Sectors

Averages of our individual-level tele-workability index across broadly defined occupations in Figure 1 are consistent with the patterns documented by the original occupational-level index developed by Dingel and Neiman (2020) and a follow-up study on worker characteristics by Mongey, Pilossoph, and Weinberg (2020) for the United States. Elementary occupations (e.g., janitors, construction laborers, street vendors) are least able to work from home, followed by plant and machinery operators and craft and related trades workers (e.g., mechanics, garments workers). At the other end of the spectrum, professionals, managers, officials and legislators are the occupations most amenable to working from home.

Figure 1: Tele-workability by Occupation

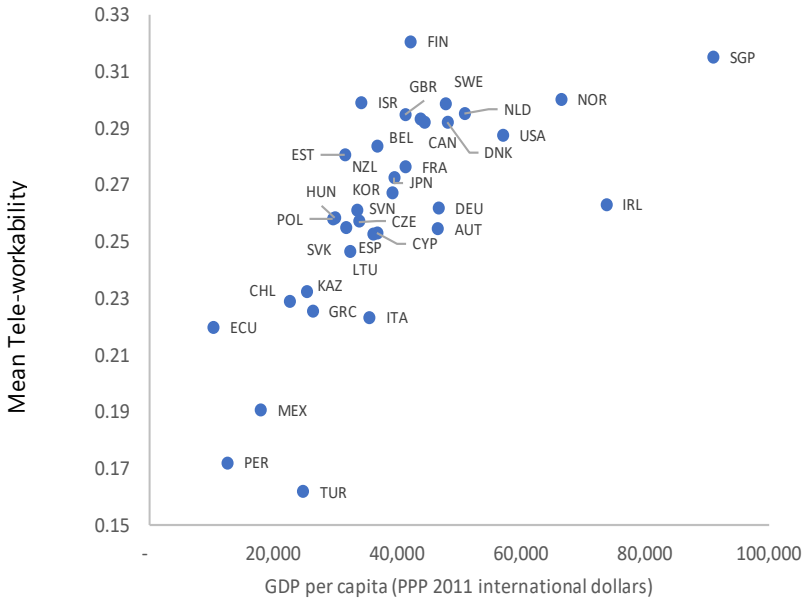


Source: PIAAC survey; Dingel and Neiman (2020); and IMF staff calculations.
Note: Dots represent average tele-workability levels across all countries. End points represent countries with smallest and largest tele-workability levels in a given category.

There is significant cross-country variation in the scope to work remotely, with Turkey exhibiting lower tele-workability scores across most occupations, suggesting that fewer jobs can be performed at home. However, rankings across occupations are broadly preserved within our sample of countries. Figure 2 shows the association between the level of economic development and the ability to work remotely. Turkey, Chile, Mexico, Ecuador, and Peru stand out with

significantly lower average tele-workability scores.[6] This suggests that workers in emerging and developing economies could face daunting challenges in continuing to work during periods of stringent lockdowns. Within advanced economies, Greece, and Italy have among the lowest tele-workability scores, while Nordic countries and Singapore have the highest scores, reflecting their relatively developed digital economies.

Figure 2: Tele-workability Index by GDP per capita (PPP)

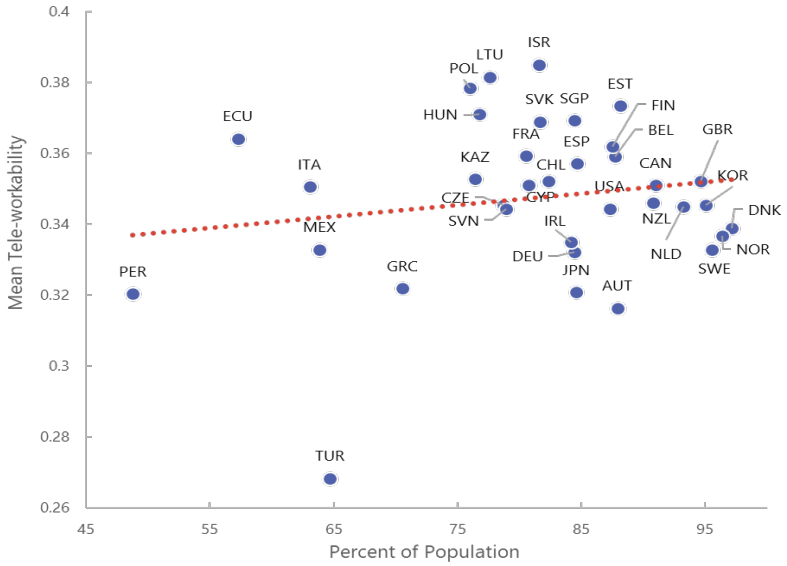


Source: PIAAC survey; Dingel and Neiman (2020); and IMF staff calculations.

An internet connection is key for working from home and is positively correlated with cross-country estimates of the tele-workability index (Figure 3). However, even in our sample of advanced and emerging market economies, only about 80 percent of population, on average, has internet access. This figure is significantly lower in emerging countries like Peru, Ecuador, Turkey, and Mexico, with well below 65 percent of population using the internet. Within Europe, Italy and Greece lag significantly behind their Nordic counterparts.

[6] For a subset of PIAAC countries, we perform a robustness check by recreating the country level tele-workability index using sector-level tele-workability weighted by value added and labor share of each sector (from EU KLEMS data) in the respective countries. Our alternative estimates for country-level tele-workability averages very closely mirror the estimates from the PIAAC sample.

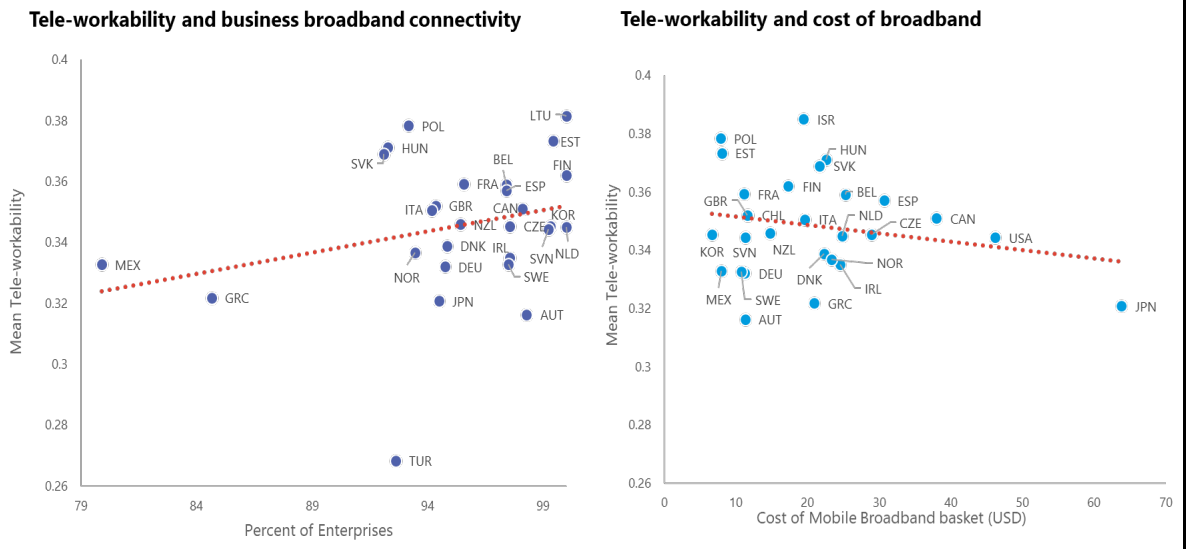
Figure 3: Tele-workability Index and Internet Usage



Source: PIAAC survey; Dingel and Neiman (2020); World Bank; and IMF staff calculations.
Note: Internet usage is defined as percent of population using Internet. Latest value available is used (2017 or 2018).

The availability of an internet connection at home, however, may not be a sufficient condition for working remotely. In countries such as Mexico and Greece, less than 85 percent of enterprises had broadband connectivity in 2016 (Figure 4). As documented in Figure 4, the average cost of a mobile broadband basket is negatively correlated with the amenability of working from home, suggesting that lack of affordable broadband connection can drive differences in firm uptake of technologies across countries.

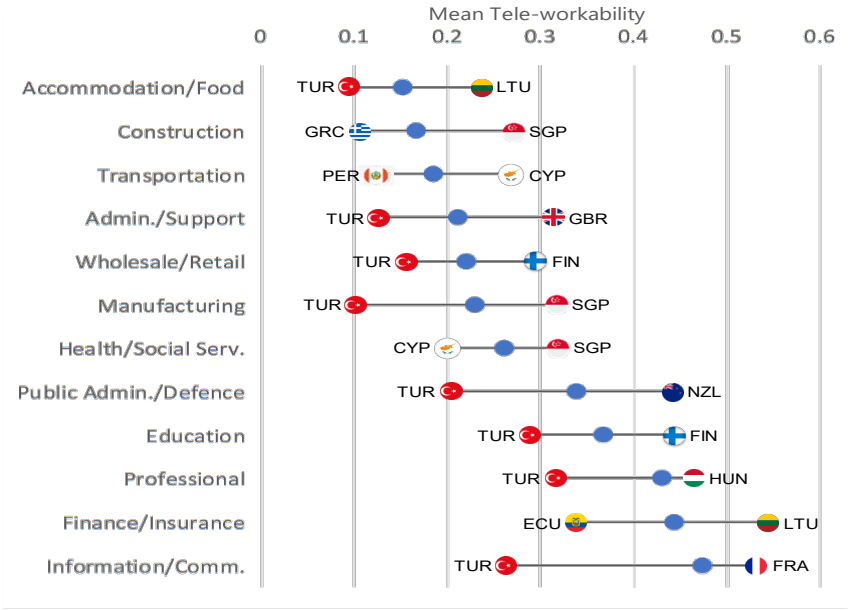
Figure 4: Broadband Internet Cost, Business Connectivity and Tele-workability Index



Source: PIAAC survey; Dingel and Neiman (2020); OECD; and IMF staff calculations.
Note: Left-hand-side chart plots average tele-workability index by country against the percentage of enterprises using broadband connection in 2016. Right-hand-side chart plots average tele-workability index by country against an average monthly cost of mobile broadband basket for a low user in 2016.

Figure 5 shows the distribution of the computed index score across different sectors. On average, workers with a lower scope for working from home are concentrated in accommodation and food services, transportation, wholesale and retail trade, health and social services, and manufacturing sectors (Figure 3). Within these sectors, however, essential activities in critical supply chains (food, pharmaceuticals, deliveries, healthcare, as well as some types of manufacturing) have been exempt from lockdown restrictions in most countries. By contrast, sectors best suited for teleworking include information and communication, finance and insurance and professional services (e.g., legal services and scientific research), as they typically require less physical proximity and have higher reliance on digital technologies. As in the case of occupations, there is a negative association between level of economic development and the feasibility to work remotely within a given sector. For instance, workers in Finland, Singapore, and Lithuania have higher index scores even in less telework-able sectors such as manufacturing and retail, given greater use of digital technologies in these countries.

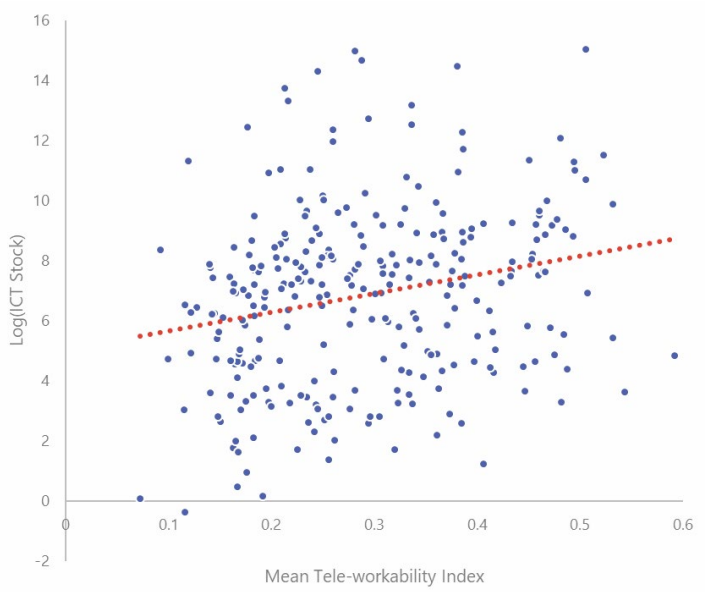
Figure 5: Tele-workability by Sector



Source: PIAAC survey; Dingel and Neiman (2020); and IMF staff calculations.
Note: Dots represent average tele-workability levels across all countries. End points represent countries with smallest and largest tele-workability levels in a given category.

Disparities in the amenability of working from home at the sectoral level are largely driven by the existing stock of ICT, including computing and communications equipment as well as computer software and databases. Figure 6 shows large variation in stocks of ICT across sector and countries. Not surprisingly, the ICT sector—the most tele-workable sector—accounts for the largest share of countries' total ICT stock. On the other side of the spectrum, accommodation and food services rely significantly less on ICT capital as an input in production, with labor accounting for the larger share in the value added.

Figure 6: Tele-workability Index and ICT Stock by Sector



Source: PIAAC survey; Dingel and Neiman (2020); EU KLEMS; and IMF staff calculations.
Note: Logarithm of ICT stock and average tele-workability index are calculated at the country-sector level. ICT stock includes computing equipment, communications equipment, computer software and databases. Countries included in the sample, for which sectoral ICT stock data is available in EU KLEMS, are Austria, Czechia, Denmark, Estonia, Germany, Greece, Finland, France, Hungary, Ireland, Italy, Japan, Lithuania, Netherlands, Slovakia, Slovenia, Spain, Sweden UK, and USA. We use the latest value available in the data (between 2015 and 2017).

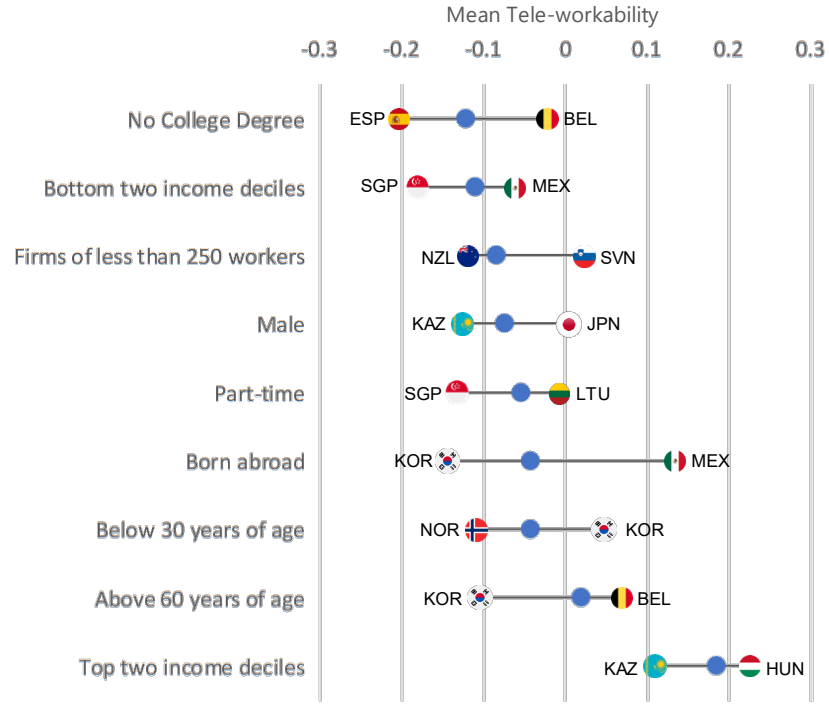
IV. Who Holds These Jobs?

We next turn to an examination of the labor market implications of social distancing policies for specific categories of workers and the resulting implications for inequality for the sample as a whole, and in individual countries. To correlate demographic characteristics with our estimate of tele-workability, we run a simple regression of the form:

$$\text{Teleworkability}_{ic} = \alpha_{ic} + \beta * X_{ic} + \gamma_c + \varepsilon_{ic},$$

where $\text{Teleworkability}_{ic}$ is an index ranging from 0 to 1 for an individual i in country c and X_{ic} a demographic variable of interest (gender, age, hourly earnings, whether born abroad, job stability, and firm size), and γ_c are country fixed effects. All demographic characteristics are expressed as binary variables and a positive coefficient β indicates higher feasibility of working from home for a given group relative to its counterpart. We plot the point estimates for each of these characteristics in Figure 7, ordering these attributes from the highest to the lowest point estimate, with ranges for different countries. Annex 2 presents country-level model estimates and *p* values, estimated using interactions of each demographic variable with a country indicator variable, to capture differences of each country from the full sample mean. Overall, our results suggest that risks of income and employment loss fall disproportionately on vulnerable groups of workers.

Figure 7: Tele-workability Index by Worker Characteristics



Source: PIAAC survey; Dingel and Neiman (2020); and IMF staff calculations.
Note: Dots represent estimates of group differences from cross-country regressions where the tele-workability index is regressed on one of the worker characteristics in the list. Each worker characteristic variable takes on values 0 or 1, indicating that an individual belongs to that group. All coefficients are statistically significant at 1 percent significance level. End points represent the smallest and largest coefficients on worker characteristics from regressions.

Gender

We find that men, on average, are less likely to be engaged in work activities that can be performed at home compared to women[7]. This outcome is related to selection of men and women into occupations and sectors (Annex 3). Men, for instance, are more likely to work as plant and machine operators and crafts and trade workers, and in construction, transportation, and manufacturing sectors. Women's employment is concentrated in the public sector and in the care and education sectors. This suggests that female workers could be less affected by the physical lockdowns and social distancing measures currently in place in many advanced and emerging countries.[8] At the same time, female workers who lack access to adequate leave in case

[7] Japan is an exception as the coefficient on 'Male' is positive implying females in the workforce are less tele-workable than men

[8] These results depend on the extent to which women have access to digital tools. Women's jobs tend to be at higher risk in countries with a larger digital gender divide (see Brussevich, Dabla-Norris, and Khalid, 2019).

of sickness or disproportionately shoulder care responsibilities may have to cut down their activities or even leave their jobs entirely.[9] Women could also be at greater risk of job loss if demand for accommodation and food services, tourism, and retail services, which account for a sizeable share of their labor force participation, particularly for low-skill workers, does not recover when social distancing measures are unwound. This is already borne out by data from the US, which shows that women's labor market prospects were disproportionately affected by the crisis (BLS, 2020).[10]

Age and Educational Attainment.

Older workers (aged 60 and above), on average, are slightly more likely to hold jobs with a high tele-workability score as compared to younger workers (under 30). This result, however, varies significantly across countries, with more than a quarter of country coefficients being negative and statistically significant. In Asian countries (Korea, Singapore, Japan) and some emerging market economies (e.g., Kazakhstan, Mexico, Chile) older workers are less likely to be engaged in jobs amenable to teleworking. This reflects broad differences in adoption of automation technologies and educational attainment of workers across countries.

Workers without a college degree are significantly less likely to work in jobs that can be performed at home relative to their more educated peers. This result holds across most countries. For a given occupation, workers with low levels of educational attainment in Spain, Italy, Ecuador and Mexico have the lowest tele-workability scores. Comparing age profiles against sectors, this higher risk for young employees is consistent with the relatively younger age profiles of the most affected sectors, such as wholesale and retail and accommodation and food services.

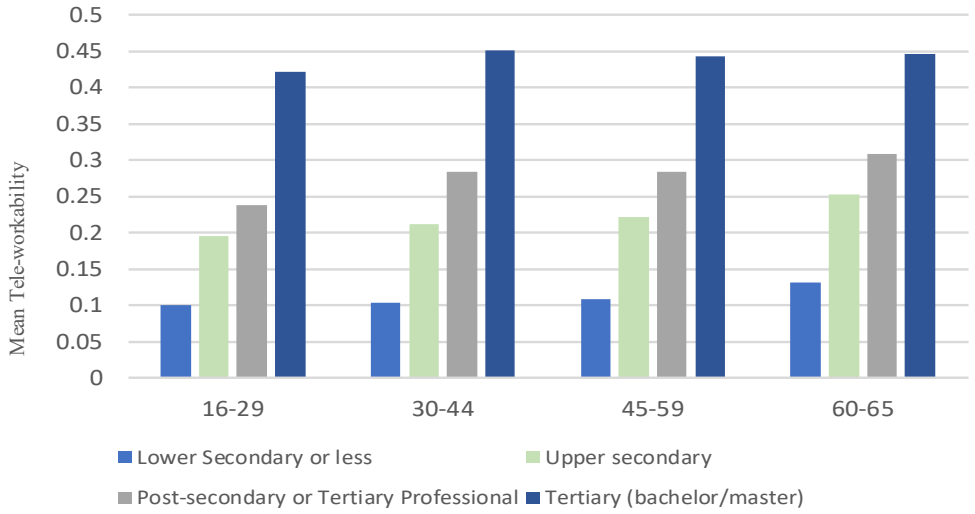
We next evaluate differences in ability to work remotely by age and education together. On average, having a college degree greatly improves the likelihood of working remotely across all age groups (Figure 8). However, older workers with lower levels of education still have higher levels of tele-workability, reflecting lifecycle effects as there is a natural progression into more senior-level occupations over a worker's career. These findings also suggest that earnings and income gaps between generations that were exacerbated by the Global Financial Crisis (Dabla-

[9] Gender gaps in unpaid work are largest in Japan and Korea (2.5 hours) and Turkey (4 hours per day), where traditional norms on gender roles prevail (Alonso et. al., 2019).

[10] Data from the US shows that the unemployment rate for women ages 16 and over rose from 3.4 percent in February 2020 to 16.2 percent in April 2020. This is 2.7 percentage points higher than the unemployment rate for men the same age (13.5 percent). The unemployment rates for women are now higher and have risen faster than the same rates for men across all age groups (BLS, 2020).

Norris, Pizinelli, and Rappaport 2019), could widen even further after the current crisis, with less educated, younger workers the hardest hit in many countries.[11]

Figure 8: Tele-workability Index by Age Group and Education Level



Source: PIAAC survey; Dingel and Neiman (2020); and IMF staff calculations.

Job Characteristics

Workers employed in part-time jobs are less likely to work remotely. Part-time workers in Singapore and Korea, in particular, have significantly lower tele-workability scores compared to those in full-time jobs. Within Europe, part-time contracts account for a sizeable fraction of total employment in Germany, UK and the Netherlands (OECD, 2020b). This is particularly the case for sectors most affected by lockdowns. Part-time and temporary workers could thus be at greater risk of job loss as it is less costly for firms to shed workers hired under non-standard contracts. At the same time, they typically have limited protection against the risk of job or income loss because of lower contributions or lack of entitlement to paid sick leave, unemployment benefits and other income support.

Workers in SMEs (with less than 250 workers), which account for close to 90 percent of jobs in our sample, are less likely to be in jobs that are amenable to teleworking compared to workers in larger enterprises. This may be a result of SMEs lagging behind larger firms in their adoption of digital technologies even in advanced economies.[12] Differences in tele-workability scores for workers in SMEs as compared to larger firms, however, are less stark in many Eastern European countries. Overall, the risk of employment loss is higher in SMEs, as smaller firms also tend to be

[11] In many European countries, for instance, incomes declined sharply for young people after the 2007 crisis due to unemployment, and only recovered very slowly, pointing to long-lasting scarring in labor markets (Chen et al. 2018).

[12] In our sample, workers in larger firms are three times more likely to have a moderate or complex level of computer use than workers in firms with fewer than 250 employees.

more liquidity constrained, have less of a capital cushion to continue paying furloughed employees, and may be less likely to survive the lockdown period. This is corroborated by recent firm surveys in OECD countries which find that half the SMEs already face severe cashflow problems, with many only having a few months reserves to withstand the crisis (OECD, 2020a; Bartik et al., 2020).

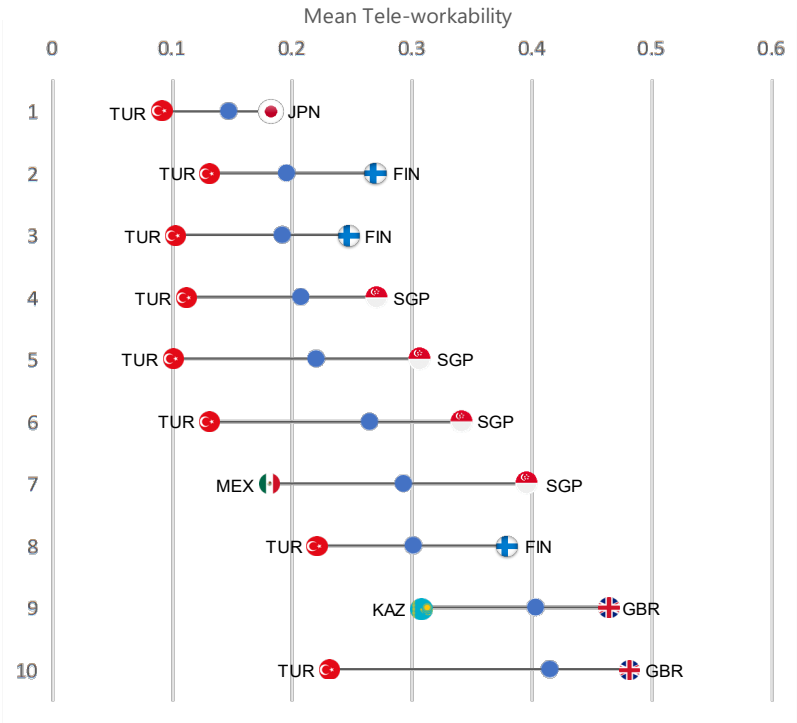
Immigration Status

Foreign-born individuals, on average, are significantly more likely to belong to occupations which are less amenable to teleworking. They also often lack access to emergency assistance and social insurance. This difference is more marked in European countries than in the United States. In Peru and Mexico, however, foreign-born workers have higher tele-workability score, on average, potentially reflecting selection of higher-skilled immigrants in emerging market countries.

Earnings Distribution

The likelihood of working in an occupation that is amenable to teleworking is also very strongly correlated with worker's hourly earnings, with workers in the bottom two deciles of the hourly earnings distribution significantly less likely to work remotely than workers in the top two deciles (Figure 9). Not surprisingly, workers in the bottom earnings quintiles are concentrated in

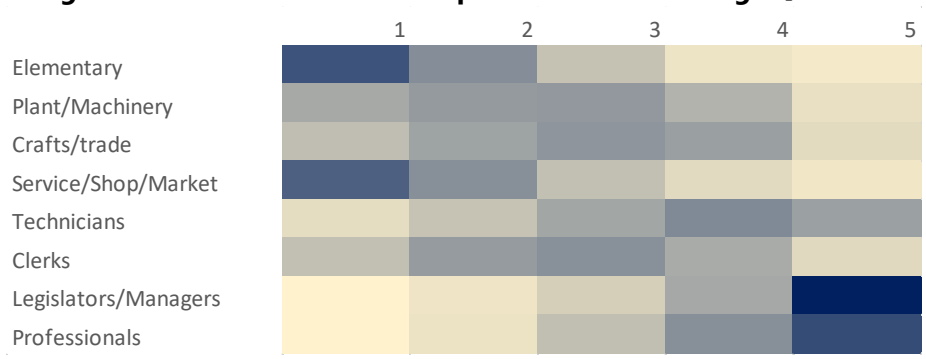
Figure 9: Tele-workability Index by Hourly Earnings Decile



Source: PIAAC survey; Dingel and Neiman (2020); and IMF staff calculations.
Note: Dots represent average tele-workability levels across all countries. End points represent countries with smallest and largest tele-workability levels in a given category.

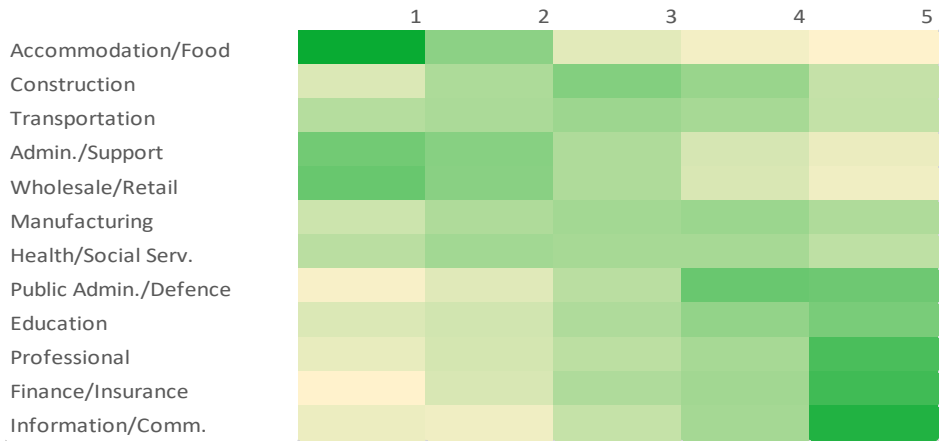
occupations and sectors where work cannot be plausibly done from home (Figures 10a-b). Across countries, workers in the bottom deciles are also more likely to live hand-to-mouth and to have lower financial buffers.

Figure 10a: Distribution of Occupations across Earnings Quintiles



Source: PIAAC survey; Dingel and Neiman (2020); and IMF staff calculations.
Note: Occupations are ordered by level of tele-workability from lowest to highest. Darker colors indicate higher concentration of workers in a given occupation in an hourly earnings quintile from bottom (1) to top (5).

Figure 10b: Distribution of Sectors across Earnings Quintiles

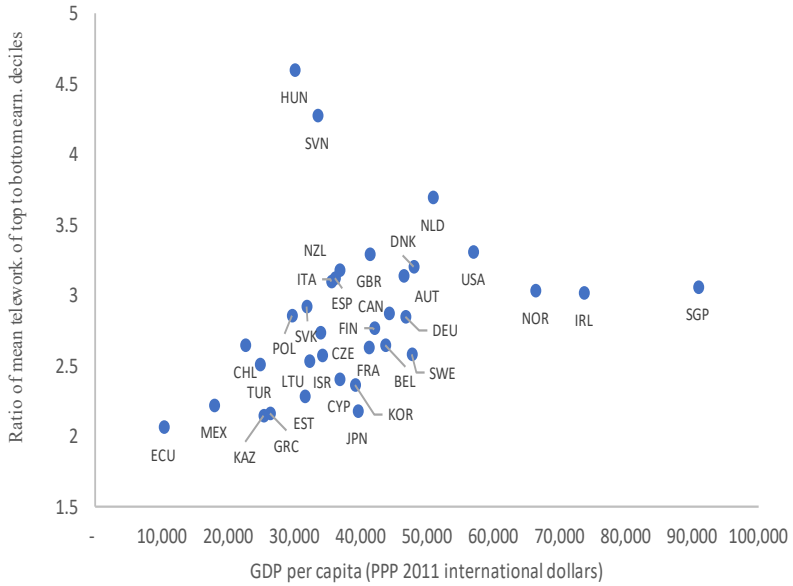


Source: PIAAC survey; Dingel and Neiman (2020); and IMF staff calculations.
Note: Sectors are ordered by level of tele-workability from lowest to highest. Darker colors indicate higher concentration of workers in a given sector in an hourly earnings quintile from bottom (1) to top (5).

Individual-level estimates of the tele-workability index also allow us to evaluate the distributional implications of the lockdown policies across countries. For each country in the sample, we compute the ratio of average tele-workability levels between top and bottom earnings deciles (Figure 11). While the average tele-workability score is significantly lower in Turkey than in Singapore (Figure 2), earnings disparity between top and bottom deciles is significantly higher in

the latter. Similarly, disparities in the ability to work from home are much wider for workers in top and bottom earnings deciles in Hungary, Slovenia, Netherlands, and the US.

Figure 11: Differences in Tele-workability between Top and Bottom Earnings Deciles across Countries



Source: PIAAC survey; Dingel and Neiman (2020); and IMF staff calculations.
Note: Each dot corresponds to the country level ratio defined as (Mean tele-workability in top hourly earnings decile)/ (Mean tele-workability in bottom hourly earnings decile).

V. Estimates of Employment at Risk

We estimate the number of workers at risk of layoff or furlough as a result of low tele-workability. Using employment reports from the US BLS, we create sector-level measures of employment changes between February 2020 and April 2020, adjusted for the average employment change for the same period during 2017–2019. We use these sectoral job losses to develop sector-specific thresholds of the index of tele-workability, such that the number of workers who have lower tele-workability than the threshold in the US sample corresponds with the number of actual employment losses recorded for the US. This allows us to pin down the thresholds of tele-workability index associated with the highest risk of job loss.

These thresholds are subsequently applied to the full sample of countries to evaluate the number of global workers who fall below the threshold and, are therefore, face a higher risk of layoffs or furloughs. In order to ensure that our global estimates are representative of the global labor force, we use International Labor Organization (ILO) estimates of employment by country and sector in 2019 for our global projections. In addition, we adjust for the country-specific stringency of the lockdown measures, using the stringency index from the Coronavirus Government Response Tracker (Oxford University, 2020). We select the highest value of the index

for April 2020 and normalize the index to the US value, given that the threshold is based on the BLS employment data.

Our results suggest that over 97.3 million workers, or more than 15 percent of the workforce, are at high risk of layoffs and furloughs due to lockdown measures in the 35 countries in our sample. US accounts for over 21 million of these jobs, or about 13 percent of employment, in line with the April 2020 BLS Employment Situation report. The worst hit sectors are restaurants and accommodation with close to 17.6 million workers at risk, and wholesale and retail with over 13.9 million workers at risk of layoffs and furloughs across 35 countries in our sample (Annex 4).

VI. Conclusions

We develop a new index of the feasibility to work from home for 35 advanced and emerging economies. We show that there are significant differences in the scope to work remotely across countries. In emerging market economies such as Turkey, Peru, and Mexico access to and use of ICT is a key impediment to teleworking. In our sample, over 97 million workers are at risk of layoffs and furlough and most of these workers are concentrated at the bottom of the income distribution.

We show that workers that are most likely to be hit by the stringent social distancing policies required to stop the spread of the pandemic differ in their demographic and socioeconomic characteristics. Across countries, those with a low score on the tele-workability index tend to be the more economically vulnerable: workers that are young, with fewer years of education, engaging in part-time work, and with earnings toward the bottom of the distribution. Many of these worker characteristics coalesce in the hardest-hit occupations and sectors. These workers are also less likely to have access to health care and the formal insurance channels that can help them weather the crisis.

The impact of COVID-19 on employment and the distribution of job losses across sectors and countries will depend on the severity and duration of containment measures and the depth and breadth of economic contractions. Evidence from past crises suggests that job losses during severe recessions can have lasting, negative effects on future earnings and job security. The impact on low-income and precariously employed workers could be particularly severe, widening income inequality within countries. Changed consumer preferences following the COVID-19 outbreak, such as greater reliance on e-commerce and altered tastes for goods and services, could also have a significant future impact on employment prospects and how work is carried out. For instance, a significant share of the demand for retail, tourism, dining out and personal services that is lost during the crisis may never return. Policy responses should appropriately account for these demographic and distributional considerations both during the crisis and in its aftermath.

Annex 1. Occupational Classifications

Occupation (ISCO 2 digit)	Occupation (ISCO 4 digit)
Professional	Science and engineering professionals
	Health professionals
	Teaching professionals
	Business and administration professionals
	Information and communications technology professionals
	Legal, social and cultural professionals
Technicians & assoc. prof.	Science and engineering associate professionals
	Health associate professionals
	Business and administration associate professionals
	Legal, social, cultural and related associate professionals
	Information and communications technicians
Legislators, senior officials, & managers	Chief executives, senior officials and legislators
	Administrative and commercial managers
	Production and specialized services managers
	Hospitality, retail and other services managers
Clerks	General and keyboard clerks
	Customer services clerks
	Numerical and material recording clerks
	Other clerical support workers
Crafts & trade	Building and related trades workers, excluding electricians
	Metal, machinery and related trades workers
	Handicraft and printing workers
	Electrical and electronic trades workers
	Food processing, wood working, garment and other craft and related trades workers
Service, shop, & market	Personal service workers
	Sales workers
	Personal care workers
	Protective services workers
Plant/machine operators	Stationary plant and machine operators
	Assemblers
	Drivers and mobile plant operators
Elementary	Cleaners and helpers
	Agricultural, forestry and fishery laborers
	Laborers in mining, construction, manufacturing and transport
	Food preparation assistants
	Street and related sales and service workers
	Refuse workers and other elementary workers

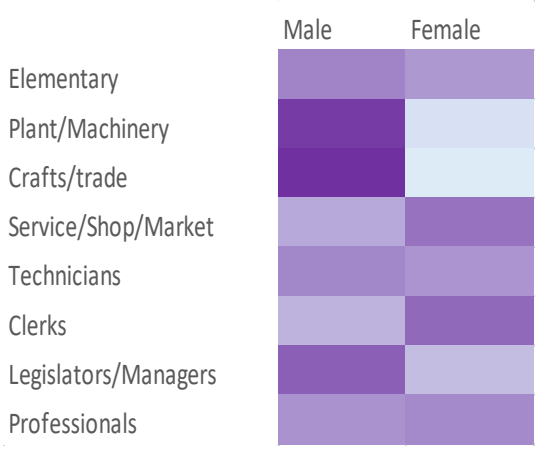
Annex 2: Country Estimates of Tele-workability Differences by Worker Characteristics

	Male	No College Degree	Below 30 years of age	Above 60 years of age	Bottom two income deciles	Top two income deciles	Born abroad	Firms of less than 250 workers	Part-time
All Countries	-0.069***	-0.115***	-0.038***	0.009***	-0.116***	0.181***	-0.067***	-0.078***	-0.057***
Austria	0.022*	0.060***	-0.009	0.023	-0.003	0.012	-0.005	0.032**	0.041***
Belgium	0.005	0.094***	0.018	0.060	-0.002	-0.012	-0.025	0.031*	0.035**
Canada	-0.018***	0.006	-0.043***	-0.004	-0.026***	-0.002	0.066***	-0.010	
Chile	-0.011	0.050***	0.033***	-0.043**	0.020*	-0.010	0.017	-0.014	0.032**
Cyprus	-0.043	0.035	0.043	-0.068	0.038	-0.049	0.055	0.047	0.019
Czechia	-0.002	0.026*	0.034**	-0.029	0.021	-0.012	0.017	0.054***	0.030
Germany	0.025***	0.063***	-0.017***	-0.010	0.002	0.036***	-0.049***	-0.015***	0.024***
Denmark	0.003	0.035**	-0.065***	0.040	-0.028*	0.012	0.013	-0.029*	0.009
Ecuador	-0.054***	-0.070***	0.024***	-0.049	0.025*	-0.038***		-0.010	-0.022
Spain	0.000	-0.092***	0.011	0.008	0.006	0.022***	-0.036***	0.015*	0.005
Estonia	-0.036	0.024	0.026	-0.008	0.006	-0.057*	-0.002	0.031	0.048
Finland	-0.005	0.058***	-0.045***	0.018	-0.010	-0.012	-0.008	0.001	0.003
France	-0.017***	0.027***	0.029***	0.010	0.018***	0.021***	-0.019***	0.021***	0.022***
United Kingdom	0.001	-0.001	-0.006	-0.008	-0.038***	0.045***	0.046***	-0.004	-0.003
Greece	-0.008	0.013	0.013	0.026	0.050***	-0.027	-0.018	0.010	-0.010
Hungary	-0.038***	-0.023**	0.034**	-0.035*	-0.013	0.046***	0.080**	0.001	-0.002
Ireland	-0.006	-0.010	-0.010	-0.053	-0.011	0.000	0.025	-0.027	-0.035*
Israel	-0.028**	-0.011	-0.049***	0.012	-0.024	0.009	0.023	-0.030*	-0.013
Italy	-0.028***	-0.089***	0.015**	0.015	0.016**	-0.014**	-0.058***	0.011	0.037***
Japan	0.084***	0.038***	-0.004	-0.059***	0.037***	-0.036***	0.088***	-0.028***	-0.032***
Kazakhstan	-0.057***	0.023**	0.079***	-0.059**	0.053***	-0.071***	-0.003	0.049***	0.024
Korea	0.050***	0.030***	0.088***	-0.118***	-0.004	-0.061***	-0.078***	-0.011	-0.050***
Lithuania	-0.051**	0.024	0.048**	-0.010	0.024	0.007	0.015	0.038	0.050
Mexico	-0.027***	-0.079***	0.033***	-0.049***	0.060***	-0.031***	0.203***	0.043***	0.033***
Netherlands	0.022***	-0.057***	-0.045***	0.000	-0.058***	0.003	0.012	-0.003	0.049***
Norway	0.024*	-0.016	-0.071***	0.024	-0.032*	-0.012	0.008	-0.006	-0.023
New Zealand	-0.016	-0.023	-0.037**	0.012	-0.031	0.028	0.083***	-0.041*	0.006
Peru	0.007	0.040***	0.057***	0.001			0.160***	-0.002	0.033***
Poland	-0.053***	0.011	0.038***	-0.017	0.003	0.004	0.145**	0.062***	0.043***
Singapore	0.004	-0.033**	0.049***	-0.084***	-0.065***	-0.011	0.096***	0.003	-0.074***
Slovak Republic	-0.027*	-0.065***	0.052***	-0.003	-0.004	-0.018	0.065	0.070***	0.011
Slovenia	-0.030	0.074***	0.007	0.060	-0.034	0.037	-0.071*	0.102***	0.032
Sweden	0.001	0.044***	-0.045***	0.017	0.003	-0.015	0.010	0.005	-0.008
Turkey	-0.017***	-0.035***	0.038***	-0.001	0.055***	-0.046***	0.000	0.051***	0.016
United States	-0.025***	0.002	-0.048***	0.071***	-0.044***	0.025***	-0.004	-0.014***	-0.029***

Note: Table contains estimates of country differences from regressions where tele-workability index is regressed on one of the worker characteristics, with an interaction term for the country capturing country differences from the full sample mean. Each worker characteristic variable takes on a value of 1, indicating whether an individual belongs to a given group, or 0. Blank cells are not estimated for a given country due to lack of variable availability in the data. Full sample of 35 countries contains 151,177 observations.

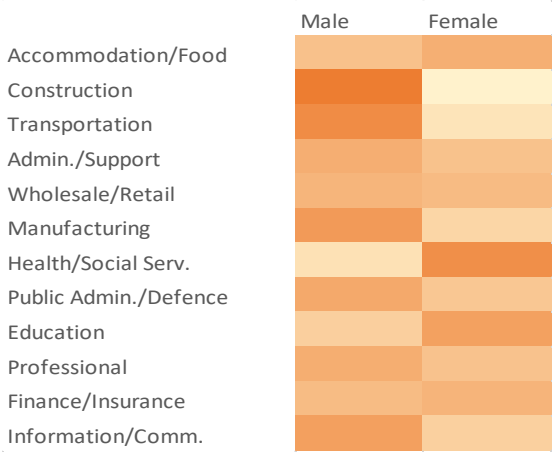
Annex 3. Gender Differences Across Sectors and Occupations

Distribution of Male and Female Workers across Occupations



Source: PIAAC survey and IMF staff calculations.
Note: Occupations are ordered by level of tele-workability from lowest to highest. Darker colors indicate higher concentration of workers in a given occupation.

Distribution of Male and Female Workers across Sectors



Source: PIAAC survey and IMF staff calculations.
Note: Sectors are ordered by level of tele-workability from lowest to highest. Darker colors indicate higher concentration of workers in a given sector.

Annex 4: Employment at Risk Estimates

Employment at Risk: Estimates by Sector

	Employment at risk (in thousands)	Share of employment at risk
Accommodation/Food Services	17,666	0.47
Wholesale/Retail Trade	13,902	0.15
Manufacturing	12,258	0.14
Other Services	11,209	0.31
Health/Social Services	9,784	0.14
Transportation	7,642	0.15
Education	7,340	0.15
Construction	6,693	0.15
Administrative/Support Activities	5,587	0.09
Public Administration/Defense	2,674	0.08
Finance/Insurance	1,414	0.07
Agriculture	936	0.03
Utilities	118	0.02
Mining	108	0.04

Source: PIAAC Survey; BLS; ILO; and IMF staff calculations.

Note: Estimates are based on the sample of 35 countries available in the PIAAC survey.

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