DOCUMENTOS DE TRABAJO

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Documento de Trabajo Nro. 263
Mayo, 2020
ISSN 1853-0168
www.cedlas.econo.unlp.edu.ar

Cita sugerida: Hatayama, M., M. Viollaz y H. Winkler (2020). Jobs' Amenability to Working from Home: Evidence from Skills Surveys for 53 Countries. Documentos de Trabajo del CEDLAS Nº 263, Mayo, 2020, CEDLAS-Universidad Nacional de La Plata.

Jobs' Amenability to Working from Home:

Evidence from Skills Surveys for 53 Countries[*]

Maho Hatayama[§] Mariana Viollaz[ł] Hernan Winkler[ʃ]

Abstract

The spread of COVID-19 and implementation of "social distancing" policies around the world have raised the question of how many jobs can be done at home. This paper uses skills surveys from 53 countries at varying levels of economic development to estimate jobs' amenability to working from home. The paper considers jobs' characteristics and uses internet access at home as an important determinant of working from home. The findings indicate that the amenability of jobs to working from home increases with the level of economic development of the country. This is driven by jobs in poor countries being more intensive in physical/manual tasks, using less information and communications technology, and having poorer internet connectivity at home. Women, college graduates, and salaried and formal workers have jobs that are more amenable to working from home than the average worker. The opposite holds for workers in hotels and restaurants, construction, agriculture, and commerce. The paper finds that the crisis may exacerbate inequities between and within countries. It also finds that occupations explain less than half of the variability in the working-from-home indexes within countries, which highlights the importance of using individual-level data to assess jobs' amenability to working from home.

JEL codes: J22, J61, O30

Keywords: Home-based-work, telework, internet, ICT, tasks.

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[*] The findings, interpretations, and conclusions in this paper are entirely those of the authors. They do not necessarily represent the view of the World Bank Group, its Executive Directors, or the countries they represent. The empirical results for the Middle East and North Africa region are part of a background paper for the report "Economic Transformation and Jobs: Making markets work for people in the MENA region" of the World Bank MNA Chief Economist Office.

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1. Introduction

The spread of COVID-19 and the implementation of "social distancing" policies around the world have raised the question of how many jobs can be done at home. Most of the existing efforts to estimate these figures rely on US-based measures of the type of tasks required by different occupations (Dingel & Neiman, 2020a; Avdiu & Nayyar, 2020; Mongey, Pilossoph, & Weinberg, 2020; Leibovici, Santacreu, & Famiglietti, 2020).[1] However, the task content of jobs exhibits substantial variation across countries (Lo Bello, Sanchez-Puerta, & Winkler, 2019; Hardy, Lewandowski, Park, & Yang, 2018). Differences in the organization of production or in the level of technology adoption across countries imply that the same occupation may be more intensive in face-to-face interactions or in physical tasks in poorer economies. As a result, using US-based measures to estimate the amenability to *working from home* (WFH) in developing countries may lead to biased conclusions.

To overcome this challenge, this paper uses skill and household surveys from 53 countries at different levels of economic development with rich information on the type of tasks carried out by people at work. We estimate indexes of the task content of jobs to rank them by their vulnerability to social distancing measures according to their amenability to a remote setup. In addition, given that the task data vary at the individual-level—and not by occupation, as in the Occupational Information Network (O*NET) classification—we show how the likelihood of being able to work from home correlates with other characteristics of the individual and his or her job.

We build on the literature by estimating jobs' amenability to WFH, as opposed to estimating the fraction of jobs that can be done at home. Estimating the latter is challenging since choosing the tasks that determine whether a person can work from home is largely arbitrary, specifically if one does not have a model linking such tasks to the probability of WFH during a pandemic. Dingel & Neiman (2020b) and Saltiel (2020) consider that an occupation cannot be performed from home if at least one of several conditions holds. For instance, in the Dingel & Neiman (2020b) study, some of categories that are sufficient to consider that an occupation cannot be done at home include "Performing for or Working Directly with the Public is very important", "Handling and Moving Objects is very important" or "Repairing and Maintaining Electronic Equipment is very important." However, occupational requirements can change during exceptional conditions. For example, while for professionals in communications or in law it is very important to have contact with the public, they can still carry out some (but not all) of their tasks using ICT (Information and Communication Technologies); craft workers for whom handling and moving objects is crucial may still be able to sell their products through e-commerce; individuals repairing equipment can still work on portable objects at home, to name a few examples. More generally, occupations comprise a bundle of tasks, and while

[1] An exception is Saltiel (2020), who uses STEP surveys.

it may be optimal to work at a specific location and in *face-to-face* (F2F) contact with the public or co-workers, suboptimal work arrangements are also feasible for some occupations, particularly during a pandemic.[2]

Another caveat of using criteria where at least one sufficient condition has to be satisfied to categorize jobs is that it is not clear how to choose the number of conditions to consider when several alternatives are available. If only one condition needs to be satisfied to classify an occupation as not being able to be done at home, then the more conditions that the researcher adds to the list, the higher are the chances that at least one of them will be satisfied by a given job. For example, one of the data sets used in this paper includes a battery of questions to measure F2F contact. Two of these questions are "How often does your job usually involve sharing work-related information with co-workers?" and "How often does your job usually involve instructing, training or teaching people, individually or in groups?" A priori, both are valid proxy variables for F2F work, but while almost 100 percent of people respond "very often" to the first question in most countries, there is substantially more variation in the responses to the latter. More generally, the more questions we consider to measure F2F, the higher the fraction of workers that would be classified as having an F2F-intensive job. Discarding questions and data based on this empirical observation is somewhat arbitrary.

There are two studies that are exceptions to the one-sufficient-condition criteria. Mongey et al. (2020) construct WFH and physical proximity measures for the United States using O*NET data. For the WFH measure, they use the same set of task variables as Dingel & Neiman (2020a, 2020b), but instead of defining binary indicators, they allow both the WFH and physical proximity measures to vary between 0 and 1. Leibovici, Santacreu, & Famiglietti (2020) construct a contact-intensity measure for the United States using occupation-level information from O*NET and aggregating the possible scores for the question about performing tasks in close physical proximity to other people. The final measure can take a value from 0 to 100.

To measure jobs' amenability to WFH, we exploit all the variables available in the data that describe job tasks related to home-based work. Instead of using a criterion based on satisfying at least one sufficient condition to classify occupations, we argue that the more (less) the conditions that are satisfied, the lower (higher) the amenability of a given job to be carried out at home. For example, according to our criteria, a job that satisfies three conditions would be less amenable to home-based-work than one that satisfies only one or two of those conditions. Accordingly, we also exploit categorical variables describing the intensity of different tasks, instead of transforming them into binary outcomes. While this approach still relies on the assumption that all

[2] As a robustness check, we construct an index following a methodology more similar to that of Dingel and Neiman (2020a, 2020b) and Saltiel (2020) where only one condition needs to be satisfied in order for a job not to be amenable to WFH and find that it is highly correlated with our WFH measures (see Figure A3).

characteristics related to the probability of working from home have the same weight, it exploits more information than a binary approach.

We use four groups of tasks to assess jobs' amenability to WFH. First, we use measures of physical intensity and manual work to capture tasks that are more likely to be location-specific—because they require handling large items or use specific equipment, for example—and cannot be done at home. Second, we use measures of F2F-intensive tasks such as those that involve supervision or contact with the public. Third, we create an index of ICT use at work, to reflect the fact that while some jobs may require substantial F2F intensity, some of such tasks can be carried out using ICT and do not necessarily have to be done in-person. Finally, and in contrast to existing studies, we also exploit information on having an internet connection at home as an important factor to determine the likelihood of a remote setup. This is important since workers in developing countries who may use ICT and have internet connectivity at the workplace, do not necessarily have access to the same resources at home. Another reason why we estimate the amenability—and not the fraction—of jobs that can be performed remotely for such a large set of countries is that several of the surveys were collected circa 2012, when internet connectivity was significantly lower than today. However, under the assumption that relative connectivity across countries or types of workers remained stable, our estimates can still be used to compare the WFH measures across these categories.[3]

We find that the social distancing measures associated with COVID-19 may exacerbate the jobs divide that preceded the crisis. The jobs intensive in tasks that are amenable to WFH are more prevalent in richer countries, and among workers with high levels of education, in salaried employment and with access to social insurance. Low-income, self-employed, and informal workers are not only less likely to do their jobs when WFH is the only option, but also less likely to have access to income protection schemes if these are channeled through the existing social security infrastructure.

Our findings highlight the importance of social protection programs to safeguard the most vulnerable during the crisis. Efforts to reach informal workers are crucial since they are less likely to have access to existing social insurance benefits, and also to additional programs launched in response to the crisis through the social security or tax administration infrastructures. Our results also show the importance of fostering technology adoption to protect jobs while respecting social distancing measures. To a large extent, the between and within country divide in WFH amenability is driven by unequal access to ICT. These benefits of digital technologies should be considered by governments in developing countries when investing in broadband infrastructure.

[3] In fact, the coefficient of correlation between the share of internet users by country in 2012 vs 2017 is 0.94 (own estimates based on data from World Development Indicators, WDI).

Finally, it is important to mention that this paper does not consider the role of essential sectors or workers (whose jobs are not affected by social distancing measures) since there is substantial heterogeneity in these policies between and within countries that cannot be fully accounted for in this paper.[4] Our individual-level measures of WFH amenability, however, can be used to assess the potential impacts of essential work policies.

The rest of this paper is structured as follows. Section 2 describes the data and the main features of the methodology. Section 3 describes the results and Section 4 concludes. The paper includes an Appendix with more detailed information on the methodology, and the estimated indexes by detailed socioeconomic group and country.

2. Data

We use three data sets covering 53 countries at different levels of development to estimate our WFH measure (see Table 1). First, we use the Surveys of Adult Skills of PIAAC (Programme for the International Assessment of Adult Competencies) for 35 countries. This survey collects information about working-age individuals and covers both rural and urban areas. Second, we use the STEP (Skills Towards Employability and Productivity) surveys for 15 developing countries.[5] The surveys are representative of urban areas (except Sri Lanka and the Lao People's Democratic Republic, which included both urban and rural areas) and collect information about working-age individuals. Finally, we use the Labor Market Panel Surveys (LMPS) for three countries in the Middle East and North Africa (MENA) region, namely the Arab Republic of Egypt, Jordan and Tunisia. These are standard labor force surveys that, in addition to the typical labor market information, also collect data about specific tasks carried out at work. Our final sample for all three data sets includes employed individuals ages 16 to 64 years.

[4] Garrote Sanchez, Gomez Parra, Ozden, & Rijkers (2020) consider the role of essential workers in their assessment of WFH measures in the European Union.

[5] We exclude China since the data are only representative of Yunnan province. There is no STEP survey for El Salvador, thereby we use instead a skills survey that includes a similar questionnaire.

Table 1. List of skills surveys

Dataset	Countries	Year
PIAAC	Austria, Belgium (Flanders), Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Ireland, Italy, Japan, Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Spain, Sweden, United Kingdom (England and Northern Ireland), United States	2011/2012
	Chile, Greece, Israel, Lithuania, New Zealand, Singapore, Slovenia, Turkey	2014/2015
	Ecuador, Hungary, Kazakhstan, Mexico, Peru	2017
STEP	Bolivia, Colombia, Lao PDR, Sri Lanka, Vietnam	2012
	Armenia, El Salvador, Georgia, Ghana, Kenya, North Macedonia, Ukraine	2013
	Serbia	2015/2016
	Kosovo, Philippines	2015
LMPS	Tunisia	2014
	Jordan	2016
	Egypt	2018

Table 2 shows the types of tasks used to estimate the WFH index, Appendix 1 describes the rationale for choosing these tasks, and Table A1 in Appendix 2 shows the complete list of variables. Such variables are slightly different across the three data sets. For example, while STEP has information on whether the job requires contact with customers, such information is not collected in the LMPS for Jordan and Tunisia. Thereby, while the indexes can be compared across countries within the STEP, PIAAC and LMPS data sets, comparisons are not possible across them.

Table 2. Description of the task indexes

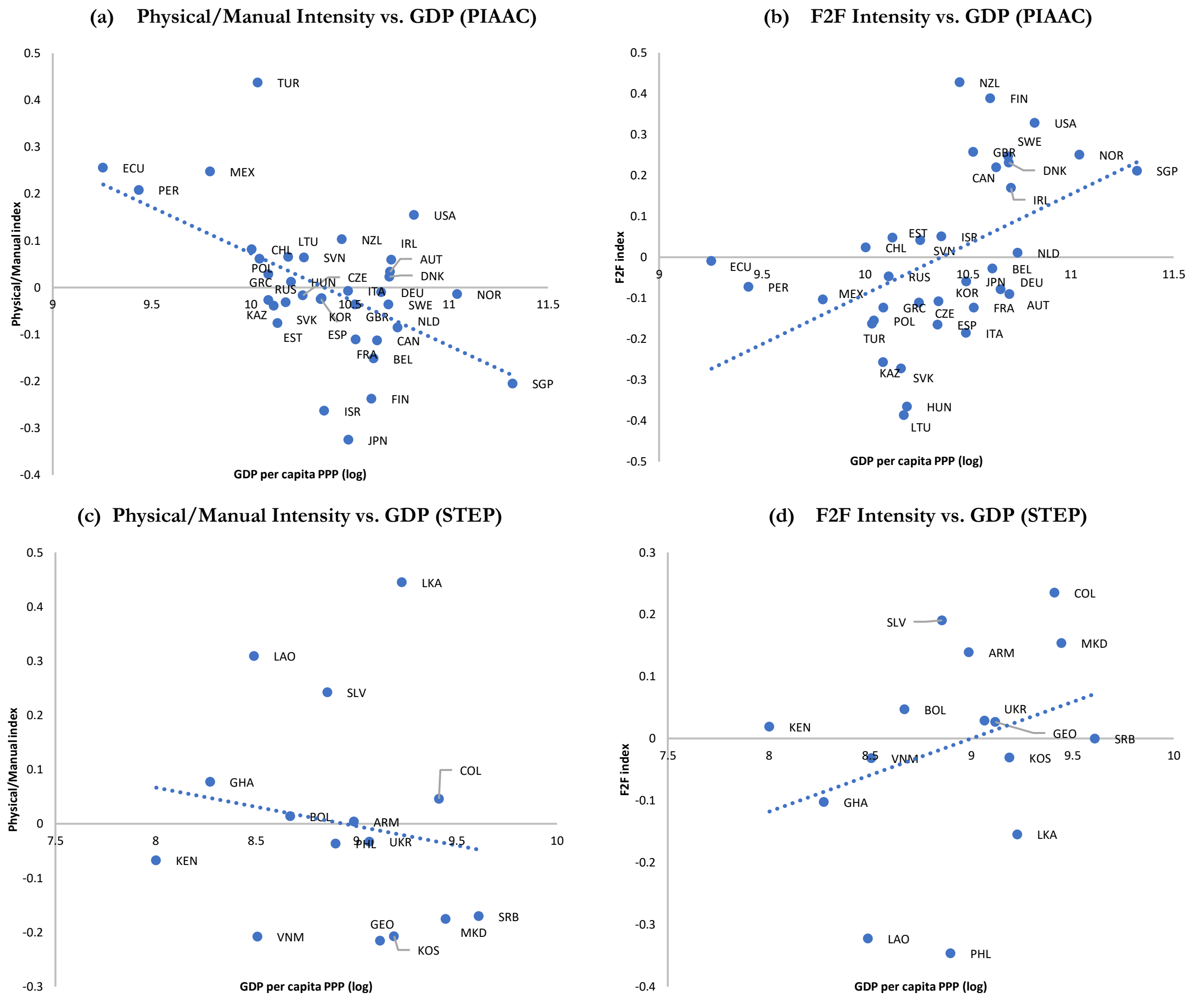
Task index	Tasks
a) Physical and manual (a higher value indicates more physical/manual intensity)	Job is physically intensive Repairing equipment Operating heavy machinery
b) Face-to-Face (F2F) (a higher value indicates more F2F intensity)	Supervising others Contact with customers, public, students
c) Low ICT use at work (a higher value indicates lower ICT use at work)	Low or no computer use at work Low or no cell phone use at work
d) Low ICT at home (based on a dummy variable equal to one if the home has no internet connection)	No internet connection at home
e) WFH (a higher value indicated higher WFH amenability)	Combination of Physical/Manual, F2F, Low ICT use at work, multiplied by -1
f) WFH adjusted (a higher value indicated higher WFH amenability)	Combination of Physical/Manual, F2F, Low ICT use at work, Low ICT at home, multiplied by -1

3. Results

3.1 Cross-country results

Figure 1 shows the correlation between the physical/manual and F2F task indexes and GDP per capita. The magnitude of the indexes is equivalent to the number of standard deviations above/below the average worker among all the countries in the sample. For example, a physical/manual index equal to 0.45 in the case of Turkey (Figure 1, panel (a)) means that jobs in Turkey are on average 0.45 standard deviations above that of the average worker among PIAAC countries in terms of physical/manual intensity. Richer countries have jobs less intensive in physical/manual skills (Figure 1, panels (a) and (c)). This factor would tend to reduce the amenability of jobs to be done at home disproportionately among poorer countries, given that their jobs would tend to be more location or equipment-specific according to this measure. In contrast, the intensity of jobs in F2F tasks tends to increase with economic development (Figure 1, panels (b) and (d)). This is driven by jobs intensive in non-routine interpersonal tasks, whose duties require more supervision or contact with the public.

Figure 1. Physical/Manual and F2F intensity, by GDP per capita

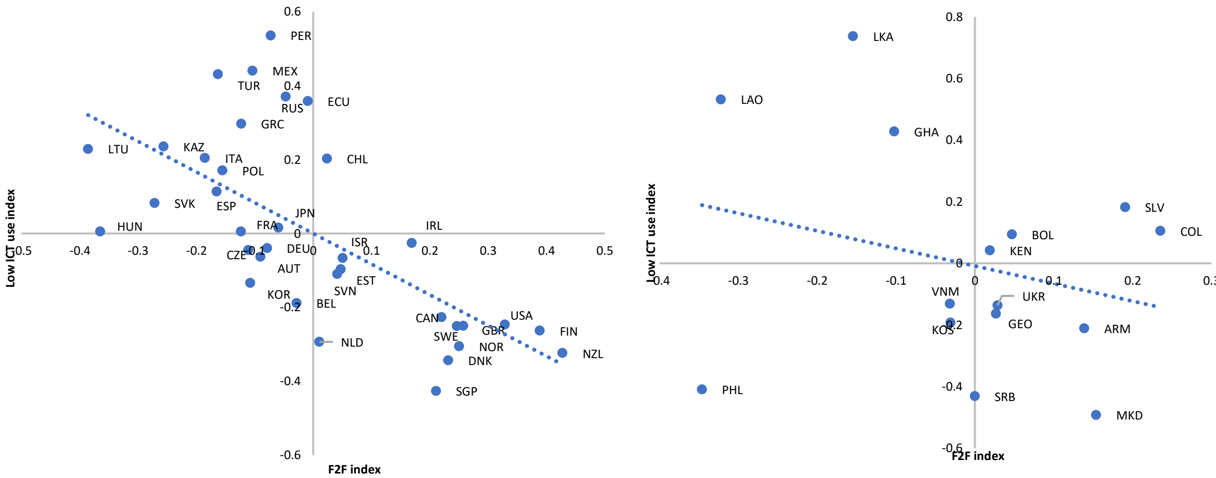


Note: The vertical axis measures the corresponding task index, in standard deviations from the mean for all PIAAC/STEP countries. GDP per capita PPP comes from the World Development Indicators (WDI) and corresponds to the same year of the respective PIAAC and STEP surveys.

The fact that the intensity of jobs on physical/manual tasks tends to decline with economic development, and that the intensity on F2F tasks shows the opposite pattern suggests that two opposing forces are at play when shaping the relationship between WFH measures and GDP per capita. However, F2F occupations also tend to be more intensive in ICT use. As seen in Figure 2, countries such as Singapore or the United States that have jobs more intensive in F2F tasks also use more ICT at work than countries such as Lithuania or Kazakhstan. That is, several of the tasks embedded in such occupations are more prone to be performed remotely. In other words, ICT use at work would tend to weaken the effect of F2F intensity on WFH measures. This correlation between F2F tasks and ICT use at work can also be observed within countries (see Figure A1 in Appendix 2).

Figure 2. ICT use and F2F intensity across countries

(a) PIAAC surveys (b) STEP surveys



Note: The vertical axis measures the Low ICT use index (a higher value means lower ICT use at work), while the horizontal axis measures F2F contact index (a higher value means more intense F2F contact). Both indexes in standard deviations from the mean for all PIAAC/STEP countries.

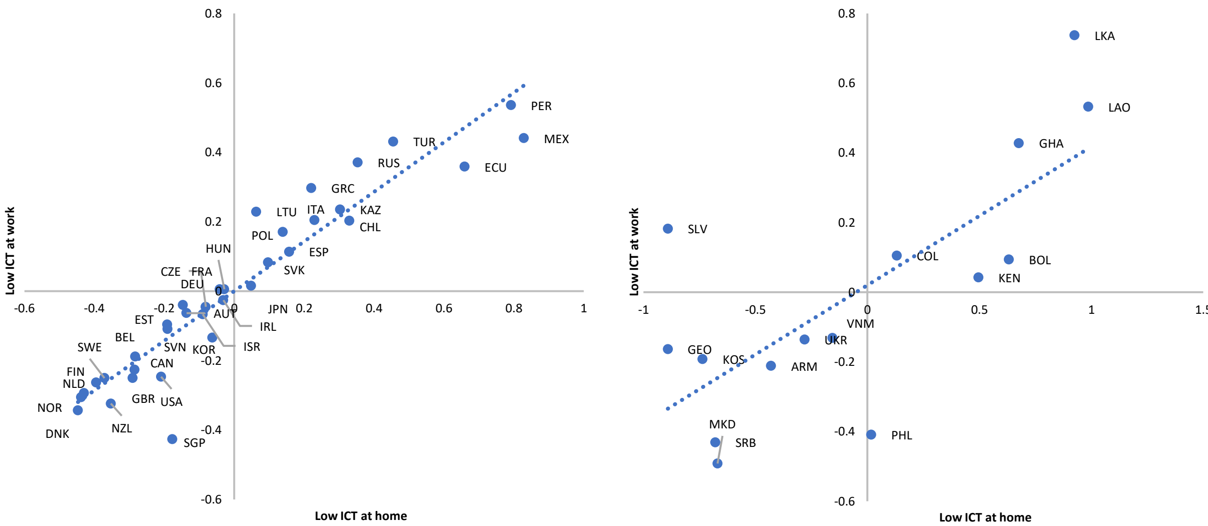
Figure 3 illustrates the importance of distinguishing between ICT use at work and the availability of an internet connection at home. While both variables are highly correlated—i.e. countries where people use more ICT at work also have higher internet connectivity at home—there are some differences, particularly among less developed countries.[6] For instance, Peru, Mexico and Ecuador are closer to the average with respect to ICT use at work, but are lagging more with respect to internet access at home. Accordingly, while the Philippines ranks relatively high in terms of ICT use at work, it has relatively low levels of internet connectivity at home (Figure 3 (b)). Thereby, while their jobs could be amenable to telecommuting based on a tasks approach, poor internet connectivity implies that many workers may not be able to do their jobs at home.

[6] While El Salvador stands out as an outlier, this could be driven by the fact that the variable to measure internet access at home is not available in its STEP survey so we use a different approach, combining two questions on having a computer and fixed telephone access at home.

Figure 3. ICT use at work and at home

(a) PIAAC surveys

(b) STEP surveys

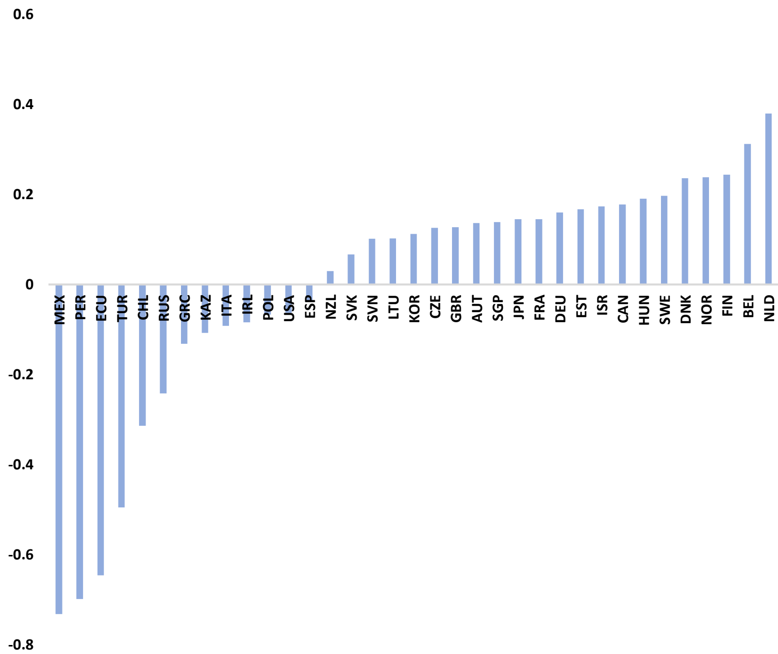


Note: The vertical axis measures the Low ICT use index (a higher value means lower ICT use at work), while the horizontal axis measures the Low ICT at home index (a higher value means poorer internet access at home). The variable to measure internet connectivity at home is not available for El Salvador, thereby we use a different approach for this country. We consider that households have internet access at home if they have a computer and fixed telephone access.

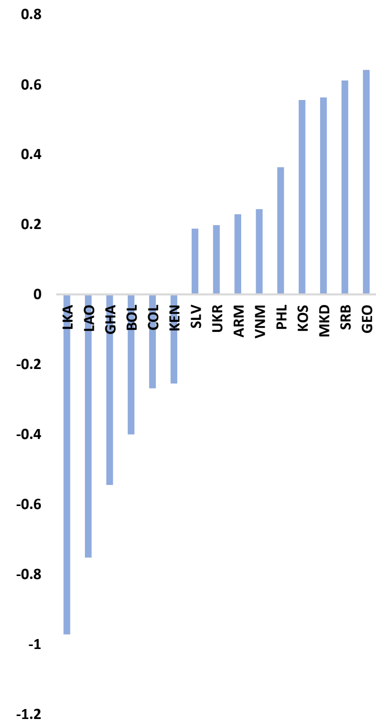
When combining the four indexes, we find substantial cross-country variation in the amenability of jobs to working from home. As seen in Figure 4, the most vulnerable countries in the PIAAC sample are Turkey and those from the LAC region. In the STEP sample, countries from the ECA region have jobs more amenable to working from home, while the opposite is true for Sri Lanka, Lao PDR, and Ghana. In contrast to Dingel & Neiman (2020a), we find that the United States ranks lower than most OECD countries in terms of its jobs' amenability to working from home. Our findings are consistent with Hardy et al. (2018), who use the PIAAC surveys and find that the United States has more jobs that are more manually intensive than most other countries.

Figure 4. WFH amenability index across countries.

(a) PIAAC surveys



(b) STEP surveys



Note: Each bar shows the number of standard deviations below/above the mean. A higher value indicates a greater amenability of jobs to working from home. The magnitude of the estimates is not comparable between the PIAAC and STEP datasets.

The difference between our results and those of Dingel & Neiman (2020a) seems to be driven by the fact that while the United States has a higher share of jobs in occupations that are more amenable to working from home than other countries, the tasks associated with these occupations are different across countries and tend to be less favorable to working from home in the United States. Figure A2 in Appendix 2 illustrates this issue using Norway, the United States and Spain as examples. The United States has 61 percent of its jobs in the four occupational categories that are more amenable to WFH, a figure higher than for Norway (55 percent) and Spain (59 percent). If we imputed the US WFH measures to each occupation of these other two countries (as in Dingel & Neiman, 2020a), we would conclude that jobs are more amenable to WFH in the United States. However, when comparing the same occupations across countries, we find that most occupations in the United States are less amenable to WFH than in Norway and Spain. For example, the US WFH index for technicians is far lower than that for Norway and Spain. In other words, these findings illustrate the importance of using measures of tasks that vary across occupations and countries, since occupations are not associated with the same tasks in different economies.

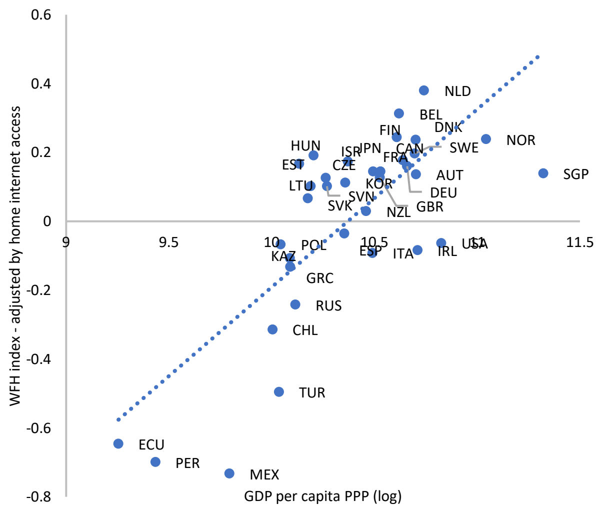
Our findings also shed light on the importance of using task measures that vary at the individual level instead of at the occupation level. A simple decomposition shows that less than half of the variation in the WFH index is explained by variation between 4-digit ISCO occupations (see Table A2 in the appendix). Most of the variation in the tasks related to WFH takes place within narrowly defined occupations.

The correlation between economic development and the amenability of jobs to working from home is positive within the PIAAC and STEP datasets. When we also consider the availability of internet access at home, the relative ranking of countries does not change significantly. That is, poorer countries have a lower share of jobs that are amenable to be done at home (Figure 5). For example, the Netherlands is 0.38 standard deviations above the average PIAAC country in terms of its jobs' amenability to working from home, while Ecuador and Turkey are 0.65 and 0.5 standard deviations below the average, respectively. In the PIAAC sample, other countries whose jobs are also more amenable to WFH are Belgium and the Nordic countries. In contrast, Peru, Mexico, and Chile have jobs that are more vulnerable in this regard. The correlation between GDP per capita and the WFH measure is negative for the LMPS countries, as Jordan ranks higher in terms of WFH amenability despite having a lower level of GDP per capita. However, this may be explained by Jordan having higher internet penetration than Egypt and Tunisia.[7]

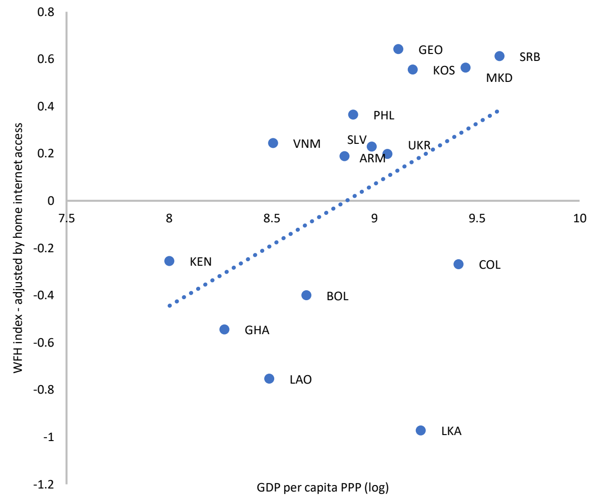
[7] According to data from the World Development Indicators, the share of internet users in the corresponding survey year was 62.3 percent in Jordan, and 46.9 and 46.1 in Egypt and Tunisia, respectively.

Figure 5. WFH amenability and GDP per capita

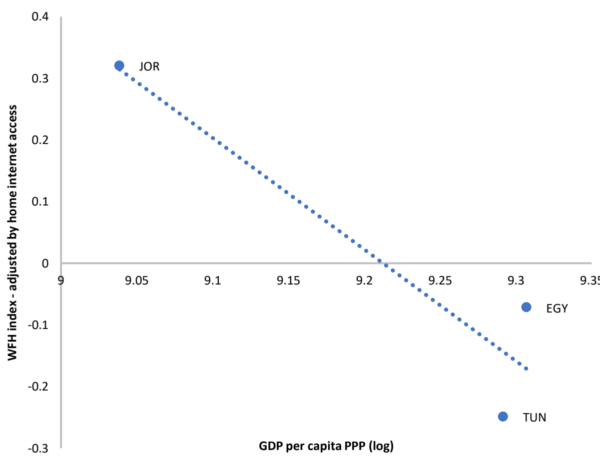
(a) PIAAC surveys



(b) STEP surveys



(c) LMPS



Note: The vertical axis measures the corresponding task index, in standard deviations from the mean of the (A) PIAAC, (B) STEP and (C) LMPS samples. A higher value indicates that jobs are more amenable to WFH.

3.2 Within-country findings

There are large disparities in terms of jobs' amenability to working from home within countries. Figure 6 shows differences with respect to the average worker for the whole PIAAC, STEP and LMPS data sets.[8] Across most countries, women are more likely to have jobs more amenable to WFH. This is because they are less likely to have jobs intensive in physical/manual work than men. Educational attainment is strongly linked

[8] Tables showing country-level findings are available in the Online Appendix (http://www.hernanwinkler.com/uploads/5/5/1/1/5511764/appendix_jobs_amenability_to_wfh_v13.xlsx).

to WFH amenability, since college graduates in all 53 countries have jobs more amenable to WFH than their less educated peers.

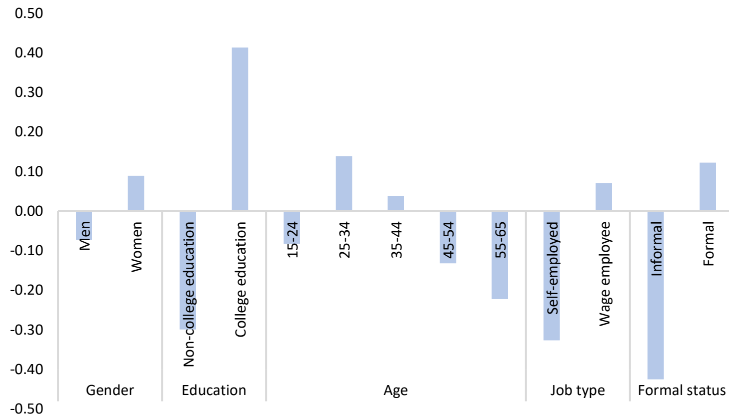
Older workers are less likely to have jobs' amenable to WFH in most countries, and this is due to a combination of counteracting forces. On the one hand, the F2F intensity increases and ICT use declines with age, which tends to reduce older workers' jobs amenability to WFH. On the other hand, the physical/manual intensity declines with age, making jobs of older workers more amenable to WFH. However, the latter is not strong enough to counteract the role of F2F and ICT tasks for older workers.

Self-employment is associated with lower amenability to WFH in most countries. Their jobs require more physical/manual intensity and require more F2F interaction. On the other hand, they are more likely to use ICT at work than salaried workers, but this factor does not affect their WFH measure to a large extent.

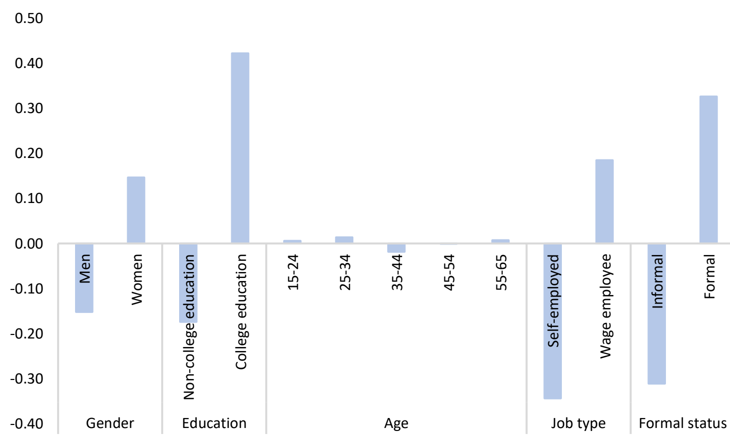
Workers with a formal job—either because they have a contract (PIAAC) or social security contributions (STEP and LMPS)—are more likely to have jobs amenable to WFH than their informal counterparts. This is because informal workers have more physical/manual intensive jobs and lower ICT use at work. This is important because informal workers are less likely to be protected against important risks. For example, subsidies and other forms of assistance during the COVID-19 crisis are easier to implement when using the social insurance infrastructure, which often only includes formal workers.

Figure 6. WFH (adjusted for home internet access), by individual characteristics.

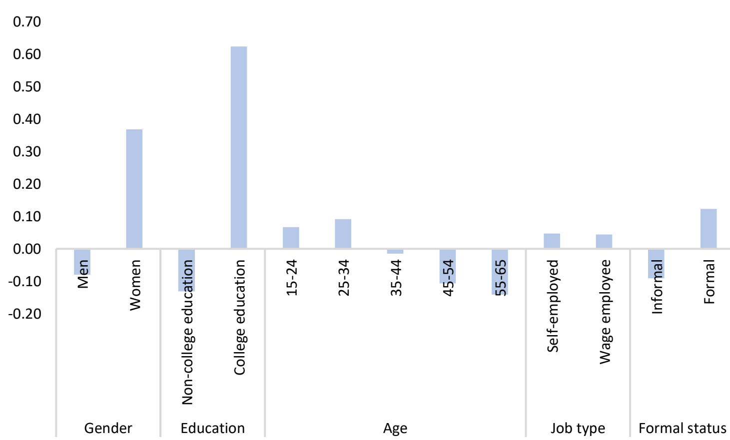
(A) PIAAC



(B) STEP



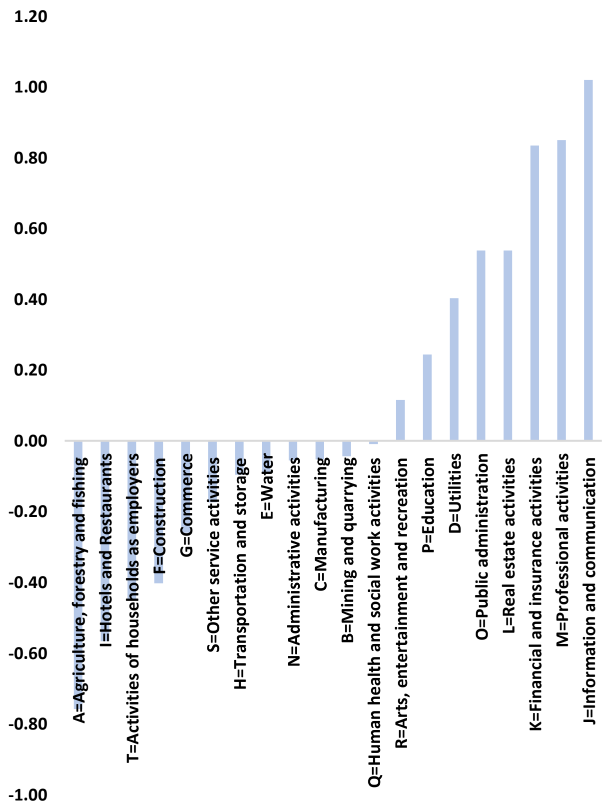
(C) LMPS



Note: The vertical axis measures the WFH index adjusted by internet access at home, in standard deviations from the mean of the (A) PIAAC, (B) STEP and (C) LMPS samples. A higher value indicates that jobs are more amenable to WFH.

The sectors that emerge as more amenable to WFH tend to be the same across most countries in the PIAAC and LMPS data sets. These sectors include ICT, professional services, the public sector, and finance (Figure 7). In contrast, jobs in hotels and restaurants, agriculture, construction, and commerce are the least amenable to WFH.

Figure 7. WFH index by sector of economic activity, PIAAC sample



Note: The vertical axis measures the WFH index adjusted by internet access at home, in standard deviations from the mean of the PIAAC sample. A higher value indicates that jobs are more amenable to WFH.

Finally, we regress the WFH index for each data set on individual and job characteristics and confirm that even after controlling for observable characteristics, women, college graduates and salaried workers are more likely to have jobs amenable to WFH than men, lower educated, and self-employed workers (Table 3).[9] Differences in educational attainment predict large gaps in WFH measures: the jobs of college graduates are

[9] Tables showing country-level findings are available in the Online Appendix (http://www.hernanwinkler.com/uploads/5/5/1/1/5511764/appendix_jobs_amenability_to_wfh_v13.xlsx).

0.70 standard deviation more amenable to WFH than those of their less educated counterparts in the PIAAC sample. That figure for the MNA region is 0.61. In all three samples, workers aged 25 and older have jobs less amenable to WFH than those 24 years or younger. In PIAAC countries, the relationship between amenability to WFH and age has an inverted U-shaped pattern, where those aged 25 to 34 years have the jobs most amenable to WFH, while those younger than 25 and older than 55 are at the opposite end. Among countries in the STEP and LMPS data sets, workers in the youngest age bracket have the jobs most amenable to WFH, but there are little differences by age among those aged 25 to 65.

Table 3. OLS regression of the WFH index (adjusted for home internet access)

	PIAAC	STEP	LMPS
Women	0.0611	0.282	0.38
	[0.00613]***	[0.0118] ***	[0.0167]***
College education	0.702	0.429	0.615
	[0.00642]***	[0.0136] ***	[0.0173]***
25-34	0.305	-0.117	-0.0788
	[0.0141]***	[0.0182] ***	[0.0213]***
35-44	0.302	-0.146	-0.144
	[0.0121]***	[0.0190] ***	[0.0215]***
45-54	0.224	-0.157	-0.162
	[0.0119]***	[0.0196] ***	[0.0229]***
55-65	0.0747	-0.138	-0.139
	[0.0122]***	[0.0232] ***	[0.0292]***
Wage employee	0.204	0.117	0.0471
	[0.00870]***	[0.0138] ***	[0.0155]***
Constant	-1.045	-0.220	-0.297
	[0.0264]***	[0.0192] ***	[0.0240]***
Observations	138,954	20,259	22,088
R-squared	0.21	0.320	0.148

Notes: All models include country fixed effects. Robust standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

4. Concluding Remarks

This paper provides new evidence on which countries and types of workers have jobs that are less amenable to working from home. Using data from 53 countries on the types of tasks that each person does at work—as opposed to occupation-level measures from the United States—it finds that poorer countries and workers who are male, with lower levels of education, self-employed, and with informal jobs are more vulnerable to social distancing policies, since the nature of their jobs makes them less amenable to working from home. These findings highlight the importance of income protection policies for workers who are not in the formal sector and thereby are less likely to be reached by social protection programs channeled through formal mechanisms. At the same time, it highlights the importance of accelerating ICT adoption to facilitate home-based work when working on-location is not an option. Finally, it shows that using individual information on the tasks that people do at work is important, since occupations capture only half or less of the types of tasks that workers do on-the-job.

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Appendix 1. Measuring the amenability of jobs to working from home

If data constraints did not exist, we argue that the probability that a job can be done at home during the COVID-19 can be modeled as:

$$\Pr(WFH = 1) = F(x, z, \varepsilon)$$

Where WFH is a dummy variable equal to 1 if the job cannot be done at home, and zero otherwise; x and z are vectors of observable and unobservable variables summarizing characteristics of the job, and ε is a random term. The observable characteristics of the job may include the extent to which it requires special equipment, supervision of others, etc. Unobservable characteristics include whether the job is considered essential by local authorities, whether the employer can financially support remote operations, etc. These variables can be summarized in a latent variable y^*:

$$y^* = x'\beta + z'\gamma + \varepsilon$$

Where

$$WFH = 1 \text{ if } y^* > 0,$$

$$WFH = 0 \text{ if } y^* \leq 0,$$

The vectors of parameters β and γ can be thought of as weights. For example, lifting heavy items at work may be a more important factor to determine the probability to WFH than having to repair equipment.

If we observed WFH during the COVID-19 crisis and had information on the job's characteristics x before the crisis, the vector of parameters β could be estimated using a standard binary choice model. However, since data on WFH are not available, we only have data on x to rank jobs by their likelihood to be done remotely. Thereby, we need to make assumptions about the values of the weights β.

We construct four indices that can be interpreted as latent variables for the probability of not working from home during COVID-19:

(1) Physical/Manual: $PH = f(p)$
(2) Face-to-face: $F2F = f(f)$
(3) Low ICT use at work: $Low\ ICT\ work = f(iw)$
(4) Low ICT at home: $Low\ ICT\ home = f(ih)$

Where p, f, iw and ih are vectors of tasks. The Physical/Manual index reflects the fact that some jobs are intensive in tasks that are location-specific and cannot be performed remotely. Examples include low-skilled jobs in mining, cleaning or in a capital-intensive manufacturing, middle-skilled jobs in equipment repairs, and high-skilled jobs that require specialized equipment such as in laboratory research. The F2F index measures the extent to which jobs require in-person interactions, that is those where the worker must be in the same place as his or her co-worker(s), supervisor, subordinate, customer, public or students.

To distinguish between face-to-face interactions that must be carried out in-person as opposed to those that can be done remotely, we construct a third index to reflect the fact that some of these face-to-face interactions can be done using Information and Communication Technologies (ICT), i.e. the low ICT at work index. Finally, we create a fourth index to capture the availability of an internet connection at home (low ICT at home index).

The WFH index is a combination of the physical/manual task index, the F2F index, the low ICT at work index and the low ICT at home index. The later captures the lack of internet connectivity at home. This is important since many workers may carry out activities that can be easily done at home, but the lack of connectivity could make it impossible.

A limitation of the data is that ICT use increased dramatically since the time that several of the surveys were collected. Assuming that the share of ICT users remained stable is not consistent with reality, since the share of internet users increased by about 65 percent in low and middle-income countries since 2012, the year of the oldest survey of our dataset.[10] Thereby, this is another reason for which is not possible to estimate the fraction of jobs that can be conducted currently using ICT. However, under the weaker assumption that the relative use of ICT across countries, types of jobs or workers remained stable over time, we provide new insights on what type of workers and jobs are more vulnerable to social distancing measures.

The components of each vector, for each dataset, are listed in Table A1. We first standardize each variable within each vector with mean zero and variance one. We then proceed to sum up all the variables within each vector and normalize the sum again to have mean zero and variance one. As mentioned above, each component within tasks receives the same weight. All four indexes are constructed so that higher values indicate a lower amenability to WFH. For example, a higher value of the physical/manual index contributes to reduce the amenability to WFH.

Then, we proceed to estimate the WFH index using the standardize indexes PH, F2F, Low ICT work and Low ICT home. We multiply the sum of the four subindexes by -1 so that a higher value of WFH indicates a higher amenability to WFH. Each of these four components are also given equal weights. That is, an increase in one standard deviation in either of the four tasks measures has the same impact on the WFH index. All the

[10] According to data from the World Development Indicators (WDI), the share of internet users in low and middle income countries increased from 26 to 43 percentage points between 2010 and 2017 (https://data.worldbank.org/indicator/IT.NET.USER.ZS?locations=XO).

standardizations are done within the PIAAC, STEP and LPMS datasets, by pooling the surveys for all the countries, to allow for cross-country comparisons.

Appendix 2. Additional tables and figures

Table A1. Variables capturing tasks for each dataset

A. PIAAC Surveys

Task Index	Variables	Type of variable
Physical & Manual index	How often does your job usually involve working physically for a long period?	Frequency
	How often does your job usually involve using skill or accuracy with your hands or fingers?	Frequency
Face-to-face index	How often does your job usually involve sharing work-related information with co-workers?	Frequency
	How often does your job usually involve instructing, training or teaching people, individually or in groups?	Frequency
	How often does your job usually involve making speeches or giving presentations in front of five or more people?	Frequency
	How often does your job usually involve selling a product or selling a service?	Frequency
	How often does your job usually involve advising people?	Frequency
	How often does your job usually involve persuading or influencing people?	Frequency
	How often does your job usually involve negotiating with people either inside or outside your firm or organisation?	Frequency
Low ICT at work index	Do you use a computer in your job? This includes cellphones and other hand-held electronic devices that are used to connect to the internet, check e-mails etc.	Yes/No
	In your job, how often do you usually use email?	Frequency
	In your job, how often do you usually use the internet in order to better understand issues related to your work?	Frequency
	In your job, how often do you usually conduct transactions on the internet, for example buying or selling products or services, or banking?	Frequency
	In your job, how often do you usually use spreadsheet software, for example Excel?	Frequency
	In your job, how often do you usually use a word processor, for example Word?	Frequency
	In your job, how often do you usually use a programming language to program or write computer code?	Frequency
	In your job, how often do you usually participate in real-time discussions on the internet, for example online conferences, or chat groups?	Frequency
Low ICT at home index	In everyday life, how often do you usually use email?	Frequency
	In everyday life, how often do you usually use the internet in order to better understand issues related to, for example, your health or illnesses, financial matters, or environmental issues?	Frequency
	In everyday life, how often do you usually Conduct transactions on the internet, for example buying or selling products or services, or banking?	Frequency
	In everyday life, how often do you participate in real-time discussions on the internet, for example online conferences or chat groups?	Frequency
	In everyday life, how often do you use spreadsheet software, for example Excel?	Frequency
	In everyday life, how often do you use a word processor, for example Word?	Frequency
	In everyday life, how often do you use a programming language to program or write computer code?	Frequency
WFH adjusted index	Physical & Manual index	
	Face-to-face index	
	Low ICT at work index	
	Low ICT at home index	
	(multiplied by -1)	

Note: PIAAC surveys also collect information on whether a person manage or supervise other workers and about the proportion of time cooperating or collaborating with coworkers. The supervision variable only applies to self-employed people. The cooperation/collaboration variable has several missing values in all countries. We decided not to include any of these two variables in the F2F index.

B. STEP Surveys

Task Index	Variables	Type of variable
Physical & Manual index	As part of this work do you regularly have to lift or pull anything weighing at least 50 lbs?	Yes/No
	What number would you use to rate how physically demanding your work is?	Frequency
	As part of this work do you repair / maintain electronic equipment?	Yes/No
	As part of this work do you operate or work with any heavy machines or industrial equipment?	Yes/No
Face-to-face index	As part of this work, do you have any contact with people other than co-workers, for example with customers, clients, students, or the public?	Yes/No
	As a normal part of this work do you direct and check the work of other workers (supervise)?	Yes/No
	Using any number from 1 to 10, where 1 is little involvement or short routine involvements, and 10 means much of the work involves meeting or interacting for at least 10-15 minutes at a time with a customer, client, student or the public, what number would you use to rate this work?	Frequency
Low ICT at work index	As part of this work do you (did you) regularly use a telephone, mobile phone, pager or other communication device?	Yes/No
	As part of your work do you(did you) use a computer?	Yes/No
	How often do you (did you) use a computer at work?	Frequency
Low ICT at home index	Does anybody in the household own (in working condition) any internet connection/internet access?	Yes/No (all countries except EL Salvador)
	Does anybody in the household own (in working condition) a computer?	Yes/No (El Salvador)
	Does anybody in the household own (in working condition) a fixed telephone line?	Yes/No (El Salvador)
WFH adjusted index	Physical & Manual index	
	Face-to-face index	
	Low ICT at work index	
	Low ICT at home index	
	(multiplied by -1)	

C. LMPS

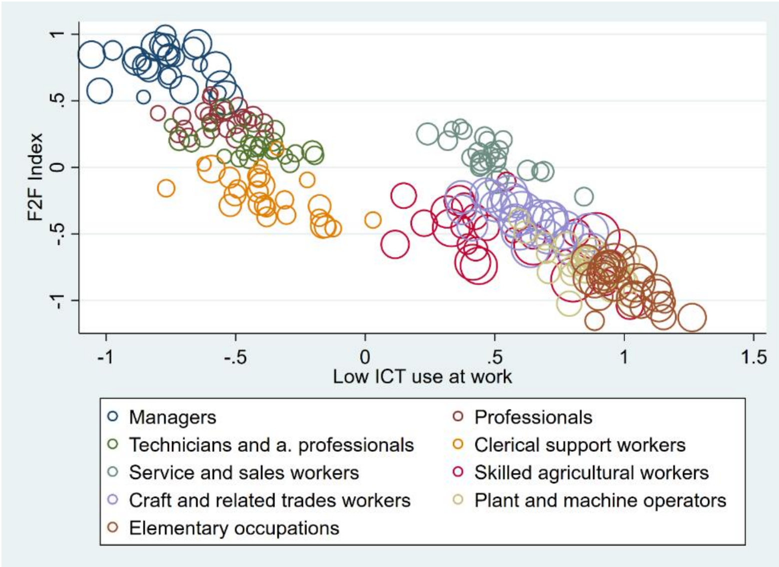
Task Index	Variables	Type of variable
Physical & Manual index	Are you exposed to bending for a long time?	Yes/No
	Does your job require physical fitness?	Yes/No
	Is the individual engaged in a craft-related job?	Yes/No
Face-to-face index	Does your job require supervising others?	Yes/No
Low ICT at work index	Do you use a computer in your work?	Yes/No
	If so, is this computer connected to the internet?	Yes/No
Low ICT at home index	Do you have access to internet at home?	Yes/No
	Does your family have internet connection?	Yes/No
	Does your family own a wireless internet router?	Yes/No
WFH adjusted index	Physical & Manual index	
	Face-to-face index	
	Low ICT at work index	
	Low ICT at home index	
	(multiplied by -1)	

Table A2. Between-within occupations variance decomposition of task indexes

	Peru	UK
Physical-manual		
Explained variance	1098.1	2470.79
Unexplained variance	3192.94	3103.47
Total	4291.04	5574.27
Explained %	26%	44%
Unexplained %	74%	56%
ICT Reverse		
Explained variance	3165.28	1723.52
Unexplained variance	2922.33	2241.61
Total	6087.61	3965.13
Explained %	52%	43%
Unexplained %	48%	57%
Face-to-face		
Explained variance	1947.61	1854.37
Unexplained variance	3080.34	3175.28
Total	5027.95	5029.65
Explained %	39%	37%
Unexplained %	61%	63%
Work-from-home		
Explained variance	2187.99	2191.44
Unexplained variance	3246.55	2636.51
Total	5434.54	4827.94
Explained %	40%	45%
Unexplained %	60%	55%

Note: Estimated using an OLS regression of each task index on a set of 4-digit ISCO dummy variables. The Between-occupations component is the share explained by the model, while the Within-occupations component is the unexplained variance (the residuals).

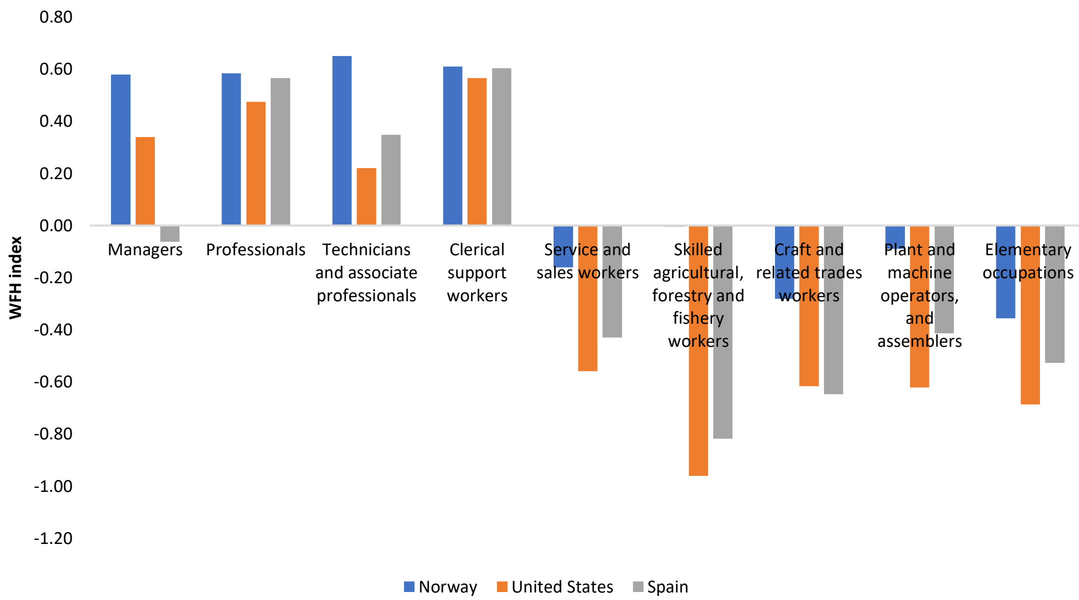
Figure A1. F2F intensity and ICT use at work, variation across occupations and countries



Note: PIAAC sample. Each bubble shows the average F2F and Low ICT use at work index for each 1-digit ISCO occupation and country. The size of the bubble is proportional to the employment share of each occupation in the country. The task indexes are residuals of a regression on country fixed effects, to net out average cross-country differences.

Figure A2. WFH index and occupational shares in Norway, US and Spain

(a) WFH index by occupation



(b) Occupation structure (% of total employment)

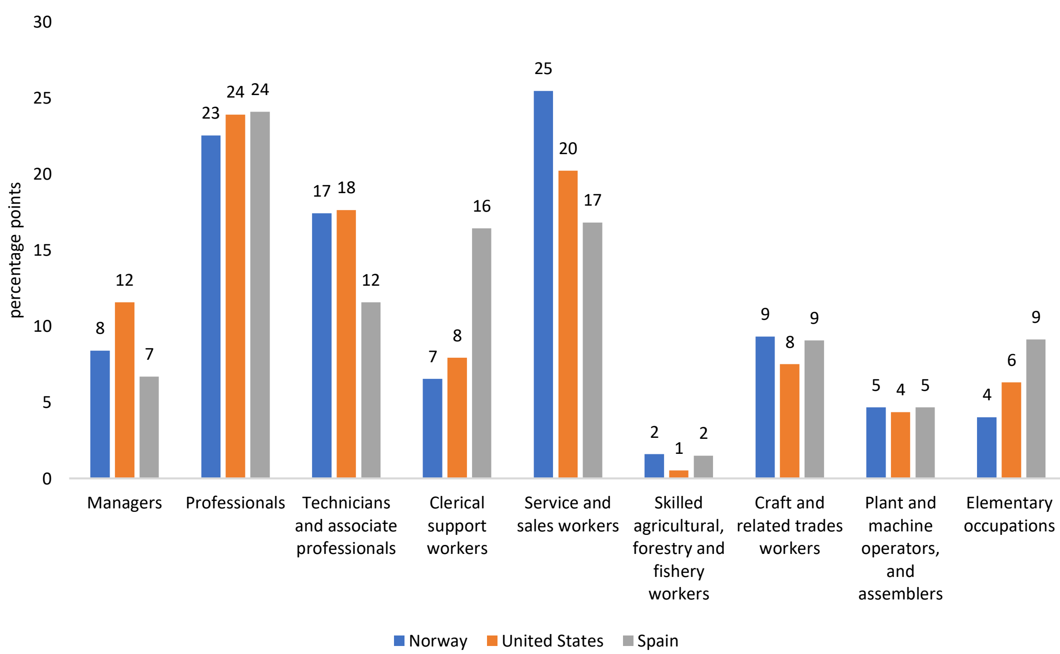
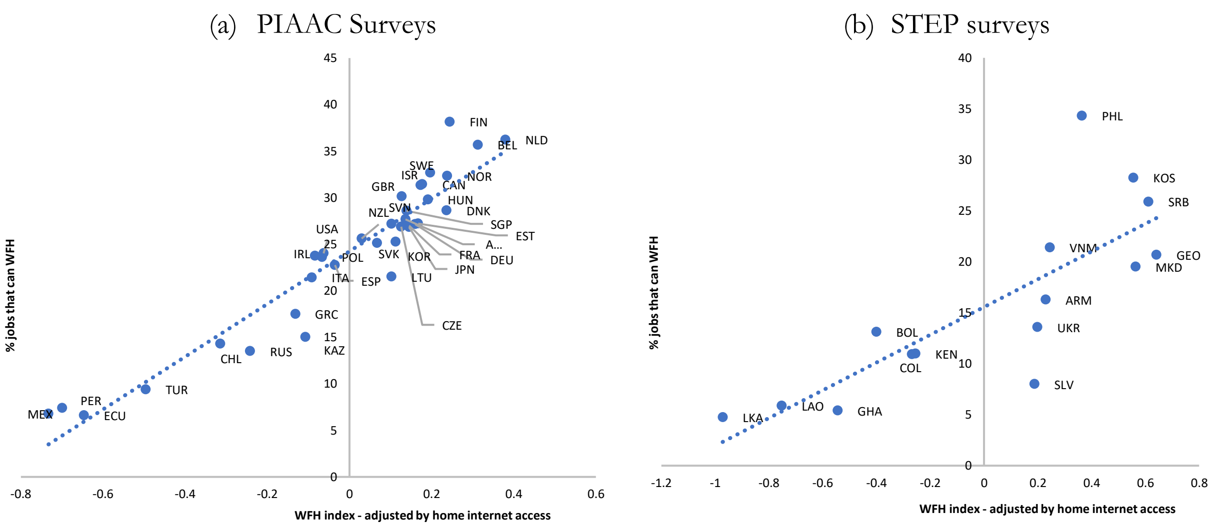


Figure A3. Correlation with Dingel and Neiman-like measures



Note: The vertical axis measures the share of jobs that can be done from home, following a methodology similar to Dingel & Neiman (2020a, 2020b). We restrict the set of task variables to those closer to the ones used by Dingel & Neiman (2020b). For the PIAAC sample, we define a job as unable to be done from home if at least one of the following conditions is met: (i) the job requires working physically for a long period at least once a week, (ii) the frequency of email use is less than once a month, (iii) the job involves selling products or services at least once a week. Using this definition, we obtained values very close to those reported by Dingel & Neiman (2020a) in Figure 2. For the STEP sample, we use the calculations obtained by Saltiel (2020).