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Jobs' Amenability to Working from Home: Evidence from Skills Surveys for 53 Countries

RESEARCH

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ABSTRACT

We use skills surveys from 53 countries to estimate jobs' amenability to working from home (WFH). Our measure combines data on self-reported jobs' characteristics and home internet access into a standardized measure. We find that jobs' amenability to WFH increases with economic development. Women, college graduates, and salaried and formal workers have jobs that are more amenable to WFH than the average. The opposite holds for workers in hotels and restaurants, construction, agriculture, and commerce. We validate our measure using longitudinal data from Chile and showing that WFH amenability correlates negatively with job losses between 2019 and 2020 and positively with the observed share of workers who worked from home in 2020. Finally, occupations explain less than one third of the variability in the WFH measure and its components, highlighting the importance of using individual-level data to assess jobs' amenability to WFH.

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1. INTRODUCTION

The spread of COVID-19 and the implementation of social distancing policies around the world raised questions about what jobs can be performed from home. This issue transcended the pandemic, though, as many recognized that working from home could remain a commonplace work arrangement in a post-pandemic world.[1] Most of the existing efforts to answer this question rely on US-based measures of the types of tasks different occupations require (Dingel and Neiman 2020; Avdiu and Nayyar 2020; Mongey, Pilossoph, and Weinberg 2021); however, the task content of jobs shows substantial variation across countries (Lo Bello, Sanchez-Puerta, and Winkler 2019; Hardy et al. 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 data to estimate work from home (WFH) measures in developing countries, as has been done by part of the existing literature (for instance, Monroy-Gomez-Franco 2021; Gasparini and Bonavida Foschiatti 2020), may lead to biased conclusions.

This paper uses skills and household surveys from 53 countries at different economic development levels, which is the largest dataset with rich information on the types of tasks people carry out at work. We estimate indexes of the task content of jobs and of having an internet connection at home, which we combine into a standardized WFH amenability measure instead of classifying jobs as feasible or not feasible with WFH as most of the previous literature, namely binary approach—that is, according to our measure, a job can be more or less amenable to WFH. Given that the task data vary at the individual level—and not by occupation, as in the Occupational Information Network (O*NET) classification for jobs in the United States—we also show how amenability to WFH correlates to other characteristics of individuals and their jobs. In addition, using longitudinal data for Chile from the Encuesta Nacional de Empleo, we validate our measure by analyzing how our WFH amenability measure correlates to job losses between 2019 and 2020 and to the share of people who reported to be working from home during the pandemic quarters of 2020. Finally, we examine the correlation between our WFH amenability measure and one obtained by applying the binary approach to our data.

Using data from 35 countries from the PIAAC survey (Programme for the International Assessment of Adult Competencies), 15 countries from the STEP survey (Skills Towards Employability and Productivity), and three countries from the Labor Market Panel Surveys (LMPS), we construct three task indexes and an index of home internet access 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 using specific equipment, for example—and cannot be performed at home. Second, we use measures of interpersonal interactions at work such as supervision or contact with the public. Third, we create an index of Information and Communication Technologies (ICT) use at work to reflect that while some jobs may require substantial interpersonal interactions, some of such tasks can be carried out using ICT and do not necessarily have to be conducted in-person. Finally, and in contrast to most previous studies, we exploit information on having an internet connection at home as an important factor to determine the likelihood of a remote setup. This addition is important, as 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.

We combine the four indexes applying a standardization procedure to obtain a WFH measure such that a higher value indicates a higher amenability to WFH. Because the task-related questions and the scale of responses offered to respondents differ between surveys, our WFH measure is comparable across countries within the STEP, PIAAC, and LMPS data sets, but comparisons are not possible across them. Another limitation related to the data is that surveys were collected

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1 Barrero et al. (2021a) find that "20 percent of full workdays will be supplied from home after the pandemic ends, compared with just 5 percent before". Ramani and Bloom (2021) report that "working patterns post pandemic will frequently be hybrid, with workers commuting to their business premises typically three days per week". Finally, Barrero et al. (2021b) find that "high rates of quits and job openings in recent months partly reflect a re-sorting of workers with respect to a newly salient job attribute – namely, the scope for remote work".

between 2011 and 2018 and ICT use increased dramatically since that period. We manage this data limitation by assuming that the relative use of ICT across countries, types of jobs, or workers remained stable over time.[2] Finally, lack of data sources that simultaneously inform about tasks performed at work and whether a worker works from home prevents us from estimating the contribution of each task index to the probability of working from home. Due to this limitation, our approach relies on the assumption that all task indexes contribute equally to the WFH amenability measure (that is, all have the same weight—a limitation common to other studies, such as Dingel and Neiman (2020)).

This study contributes to the literature on WFH measurement and on the characteristics of workers and jobs with higher WFH amenability in several ways. First, we use country-specific information on tasks performed at work. This is an important characteristic because countries differ in the tasks carried out at work and in their intensity, and using US data to estimate WFH measures may lead to biased results. Other studies have used skills surveys to construct WFH measures. For instance, Saltiel (2020) and Gottlieb et al. (2021a, 2021b) use worker-level task data from the STEP survey for 10 developing countries. Our paper uses, to our knowledge, the largest set of countries with available information on tasks performed at work.

Second, we construct a standardized measure of jobs' amenability to WFH, as opposed to applying a binary approach. Dingel and Neiman (2020), who led efforts to calculate WFH measures based on US data, and papers applying their methodology consider that an occupation cannot be performed from home if at least one of several conditions holds (for instance, see, Gottlieb et al., 2021a; Gottlieb et al., 2021b; Monroy-Gomez-Franco, 2021; Gasparini and Bonavida Foschiatti, 2020; Saltiel, 2020).[3] To construct our measure of jobs amenability to WFH, we exploit all the variables available in the data that describe job tasks related to home-based work and having internet access at home; and, instead of using a criterion based on satisfying at least one sufficient condition, we argue that the more (less) conditions satisfied, the lower (higher) the amenability of a given job to being 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.[4] Accordingly, we also exploit categorical variables describing the intensity of different tasks, instead of transforming them into binary outcomes.

Another advantage of combining the four indexes into a standardized WFH amenability measure is that occupational requirements can change during exceptional conditions like the COVID-19 pandemic. For example, while for professionals in communications or in law having contact with the public is very important, they can still carry out some (but not all) of their tasks using ICT; 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 it may be optimal to work at a specific location and in face-to-face contact with the public or co-workers, suboptimal work arrangements are also feasible for some occupations, particularly during a pandemic.

Some studies are exceptions to the one-sufficient-condition criteria. For example, Mongey, Pilossoph, and Weinberg (2021) construct a WFH measure for the United States using the same set of task variables as Dingel and Neiman (2020), but instead of defining binary indicators, they allow the measure to vary between 0 and 1. Hensvik, Le Barbanchon, and Rathelot (2020) use time use surveys to calculate the percentage of hours that were performed from home in a pre-pandemic period in the United States. Based on a pre-pandemic employment survey for Germany, Alipour, Falck, and Schüller (2020) creates a measure of whether a worker would be willing to

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

3 For example, in the Dingel and Neiman (2020) study, some categories sufficient to consider that an occupation cannot be performed 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."

4 Section 2.2 provides a discussion on the differences between methodologies.

work from home temporarily. Adams-Prassl et al. (2020) use during-pandemic surveys for the United States, Germany, and the U.K. that ask about the share of tasks that workers could do at home in their current or last jobs. Finally, Bonacini et al. (2021) create an index of attitudes toward working from home using data from the Italian equivalent of the O*NET. We add to this literature by constructing a WFH measure for a broad set of countries with different levels of economic development. Moreover, our measure captures WFH amenability based on the type of tasks carried out at work rather than using pre-pandemic information on hours of work performed from home, workers' willingness to work from home, as in Hensvik, Le Barbanchon, and Rathelot (2020) and Alipour, Falck, and Schüller (2020) (which could be capturing different types of work arrangements between occupations or differences in individual preferences), or the share of tasks workers believe they would be able to do from home, as in Adams-Prassl et al. (2020) (which could be capturing differences in individual perceptions).

Finally, we contribute to the literature by incorporating internet access at home as an input in our WFH measure. Despite ours not being the first study to use home internet access to construct a WFH measure (see Garrote Sanchez et al. (2021)), our methodology combines individual level data on having access to internet at home and on tasks performed at work instead of using tasks information at the occupation level from the United States and aggregated data on home internet access (at the country-wage quintile level), as in Garrote Sanchez et al. (2021).

Our results show that social distancing measures associated with COVID-19 and, more generally, moving to a widespread WFH strategy once the pandemic ends, may exacerbate the jobs divide that preceded the crisis. Jobs intensive in tasks that are amenable to WFH are more prevalent in wealthier countries and among workers with high levels of education, in salaried employment, and with access to social insurance. For instance, the average job in the richest PIAAC country (Singapore) is 0.14 standard deviations more amenable to WFH than the average job among all PIAAC countries, while it is 0.65 standard deviations less amenable to WFH in the poorest country (Ecuador). We also show that our WFH measure is negatively correlated with job losses between 2019 and 2020 in Chile: an increase of one standard deviation in the WFH measure is associated with a 11.3 percentage points reduced likelihood of losing the job. We also find that, in Chile, our WFH measure correlates positively with the observed percentage of workers who worked from home during the first quarters of the pandemic. Finally, we show that our WFH measure correlates positively with one obtained applying the binary approach to PIAAC and STEP data.

Our results also show the importance of fostering technology adoption to promote WFH amenability: less-developed countries lag behind with respect to home internet access, implying that poor internet connectivity may be impeding workers from performing from home their otherwise WFH amenable jobs. Governments in developing countries should consider these benefits of digital technologies when investing in broadband infrastructure.

2.DATA AND METHODOLOGY

2.1 DATA

We use three data sets covering 53 countries at different levels of development to estimate our WFH measure (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—ages 16 to 64—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 and collect information about working-age individuals. Sri Lanka and the Lao People's Democratic Republic are exceptions and include both urban and rural areas. To ensure comparability with other countries, we only consider urban observations for these two countries. 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

5 We exclude China as the data are only representative of Yunnan Province. There is no STEP survey for El Salvador, thus we use instead a skills survey that includes a similar questionnaire.

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Egypt, Jordan, and Tunisia. These are standard labor force surveys that, in addition to the typical labor market information, collect data about specific tasks carried out at work. Our final sample for all three data sets includes employed individuals ages 16 to 64 with non-missing information on the task-related variables and in the demographic and employment characteristics we use in the analysis.[6] We use survey weights throughout the analysis that we rescaled to add up to one within each country.[7] Sample sizes range between 593 observations in Sri Lanka to 16,152 in Canada.

Table 1 List of skills surveys and sample size.

DATASET	COUNTRIES	YEAR
PIAAC	Austria (3558), Belgium (3185), Canada (16152), Czech Republic (3470), Denmark (5014), Estonia (5059), Finland (3738), France (4238), Germany (3898), Ireland (3502), Italy (2717), Japan (3738), Korea (4234), Netherlands (3779), Norway (3233), Poland (4837), Russian Federation (2043), Slovak Republic (3189), Spain (3168), Sweden (3165), United Kingdom (5416), United States (3428)	2011/2012
	Chile (3340), Greece (2242), Israel (3301), Lithuania (3103), New Zealand (4095), Singapore (3833), Slovenia (2890), Turkey (2018)	2014/2015
	Ecuador (3157), Hungary (4124), Kazakhstan (3426), Mexico (3690), Peru (4973)	2017
STEP	Bolivia (1673), Colombia (1686), Lao PDR (1381), Sri Lanka (593), Vietnam (2172)	2012
	Armenia (1009), El Salvador (1219), Georgia (926), Ghana (2071), Kenya (2329), North Macedonia (1803), Ukraine (1141)	2013
	Serbia (1677)	2015/2016
	Kosovo (1163), Philippines (1630)	2015
LMPS	Tunisia (2689)	2014
	Jordan (5702)	2016
	Egypt (13697)	2018

Source: Own elaboration based on STEP, PIAAC and LMPS surveys.

Notes: Sample size indicated between parentheses. In Belgium, only the Flemish region (Flanders) participated in the PIAAC survey. United Kingdom includes England and Northern Ireland.

2.2 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 can be modeled as:

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

where *WFH* is a dummy variable equal to one 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 home internet access, 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, and so forth. Unobservable characteristics include whether the employer can financially support remote operations, whether workers have an adequate physical space to use as home office, and so on. These variables can be summarized in a latent variable y^*:

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

where

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

6 Demographic and employment characteristics include gender, age, educational level, type of employment (wage or self-employment), whether a worker has a contract (PIAAC) or social security contributions (STEP/LMPS), occupation and sector of employment. Age is not available for a subset of PIAAC countries (Austria, Canada, Germany, Hungary, New Zealand, Singapore, and the United States).

7 With this adjustment we avoid results being disproportionally determined by more populous countries.

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

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 in determining the probability to *WFH* than having to repair equipment. If we observed *WFH* and had information on the job's characteristics and home internet access *x*, the vector of parameters β could be estimated using a standard binary choice model. However, since data on both *WFH* and job's characteristics (including internet access at home) are not available, we only have data on *x* to rank jobs by their likelihood of being done remotely. Thereby, we need to make assumptions about the values of the weights β. We assume all variables contribute equally to WFH.

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

(1) Physical/Manual: $PH = f(p)$

(2) Interpersonal interactions: $IP = f(f)$

(3) Low ICT use at work: $Low\ ICT\ work = f(iw)$

(4) Low ICT at home: $Low\ ICT\ home = f(ih)$

where *p, f* and *iw* are vectors of tasks and *ih* refers to home internet access. The Physical/Manual index reflects that some jobs are intensive in tasks that are location-specific—because they require handling large items or use specific equipment, for example—and cannot be performed remotely. Examples include low-skilled jobs in mining, cleaning or in capital-intensive manufacturing, middle-skilled jobs in equipment repair, and high-skilled jobs that require specialized equipment such as in-laboratory research. The interpersonal interactions index measures the extent to which jobs require in-person interactions; that is those in which the worker must be in the same place as their co-worker(s), supervisor, subordinate, customer, public, or students. To distinguish interpersonal interactions that must be carried out in-person from those that can be performed remotely, we construct a third index to reflect that some of these interpersonal interactions can take place using ICT (i.e., the Low ICT use 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* amenability measure is a combination of the Physical/Manual task index, the Interpersonal interactions index, the Low ICT at work index, and the Low ICT at home index. The latter captures the lack of internet connectivity at home, which is important as many workers may carry out activities that can be easily done at home, but the lack of connectivity could make it unlikely.

Table 2 shows the types of tasks used to estimate the WFH amenability measure, and Table A1 in the Appendix shows the complete list of variables. Such variables are slightly different across the three data sets, and the scale of responses offered to respondents sometimes differs between them. 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. Therefore, while the indexes can be compared across countries within the STEP, PIAAC, and LMPS data sets, comparisons are not possible across them.

We proceed by first standardizing each variable within each vector—*PH*, *IP*, *Low ICT work*, and *Low ICT home*—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, each component within vectors 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 reducing the amenability to WFH. Then, we proceed to estimate the WFH amenability measure adding the standardized indexes *PH*, *IP*, *Low ICT work*, and *Low ICT home* and standardizing one more time. The outcome is multiplied by -1 so that a higher value of WFH indicates a higher amenability to WFH. Each of these four indexes are also given equal weights. That is, an increase in one standard deviation in either of the four indexes has the same

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impact on the WFH amenability measure. All the standardizations are performed within the PIAAC, STEP, and LMPS datasets by pooling the surveys for all the countries to allow for cross-country comparisons—specifically, the WFH measure can be compared across countries within each data set but not across them.

Table 2 Description of the tasks and home internet access indexes.

Source: Own elaboration.

INDEX	TASKS
Physical and manual (a higher value indicates more physical/manual intensity)	Job is physically intensive Repairing equipment Operating heavy machinery Use accuracy with hands/fingers
Interpersonal interactions (a higher value indicates more interpersonal interactions)	Supervising others Contact with co-workers, customers, public, students
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 Low or no internet use at work
Low ICT at home (based on a dummy variable equal to one if the home has no internet connection)	No internet connection at home
WFH measure (a higher value indicates higher WFH amenability)	Combination of Physical/Manual, Interpersonal interactions, Low ICT use at work, Low ICT at home, multiplied by –1

Another 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, as the share of internet users increased by about 60 percent since 2011, the year of the oldest survey in our dataset.[8] 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 into what type of workers and jobs are more amenable to WFH.

The standardization method described above differs from the binary approach in several respects. The differences between methods can be thought of as having different WFH production functions, where the standardized approach assumes perfect substituibility between tasks and the binary approach assumes they are perfect complements. Assuming perfect substituibility provides some advantages but it also has limitations. First, while a binary WFH measure can be drastically affected by the number of tasks considered in the analysis, the standardized measure is less sensitive to these changes.[9] Second, a standardized WFH measure provides more information than applying a binary approach.[10] However, assuming perfect substituibility does not allow for any complementarity across indices to take place. In the following sections we provide results using the standardized approach and we also compare the proposed WFH measure with one obtained applying the binary approach to our data.

8 According to data from the World Development Indicators (https://data.worldbank.org/indicator/IT.NET.USER.ZS), the share of internet users increased from 31 to 49 percent between 2011 and 2018.

9 If only one condition must be satisfied to classify a job as not being able to be done at home, then the more conditions the researcher adds to the list, the higher the chances are that at least one of them will be satisfied by a given job. Adding an extra condition or task to the analysis will change the value of the standardized WFH measure as well. However, because of its continuous nature, the standardized WFH measure avoids the drastic changes that may affect a binary WFH measure, that is, in the binary approach adding an extra condition could make a job moving from being able to be done from home to not being WFH amenable.

10 While the binary approach classifies jobs in two groups –that is, amenable or not amenable to WFH, the standardized approach allows jobs within each group to have different values of the WFH measure –to be more or less amenable to WFH.

3. RESULTS

3.1 CROSS-COUNTRY FINDINGS

Figure 1 shows the correlation between the Physical/Manual and Interpersonal interaction task indexes and GDP per capita.[11] The magnitude of the indexes is equivalent to the number of standard deviations above/below the average job among all the countries in the sample. For example, a Physical/Manual index equal to 0.45 in Turkey (Figure 1, panel [a]) means that jobs in Turkey are (on average) 0.45 standard deviations above the average job among PIAAC countries in terms of physical/manual intensity. Wealthier countries have jobs less intensive in physical/manual tasks (Figure 1, panels [a] and [c]). This factor would tend to reduce the amenability of jobs to be performed 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 Interpersonal interaction tasks tends to increase with economic development (Figure 1, panels [b] and [d]).[12]

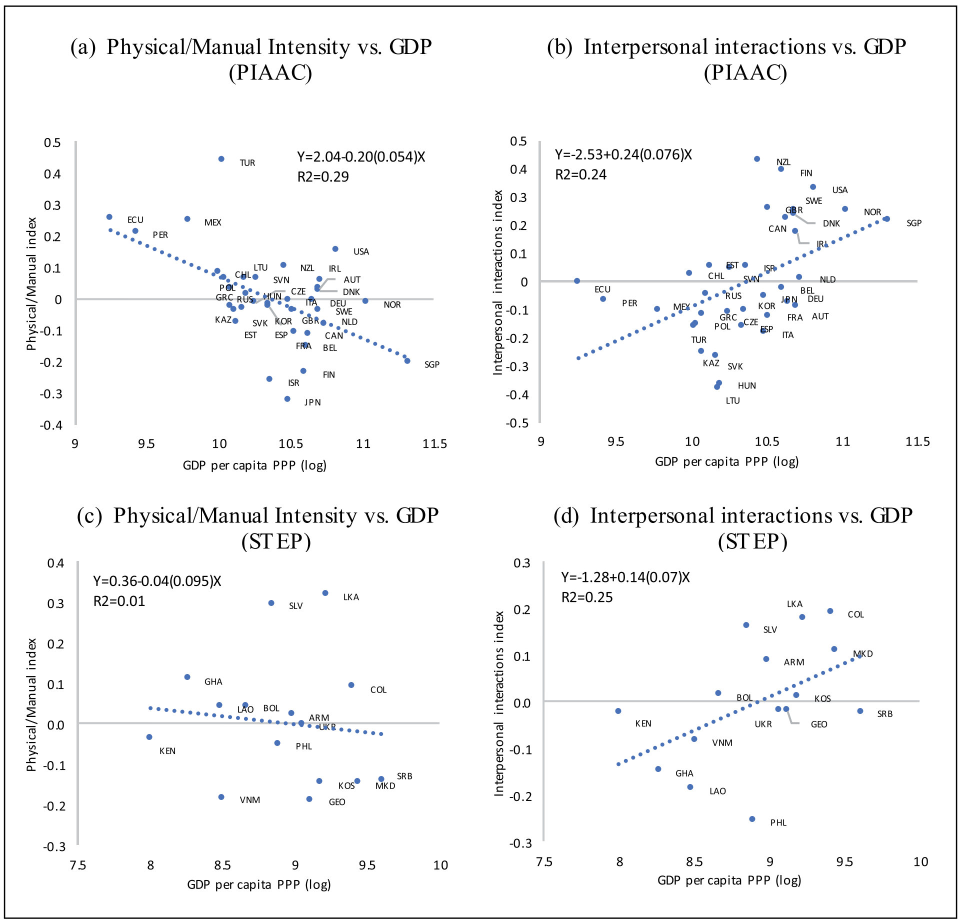

Figure 1 Physical/Manual and Interpersonal interactions intensity by GDP per capita.

Source: Own elaboration based on STEP, PIAAC, and World Development Indicators.

Notes: 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 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 interpersonal interaction tasks shows the opposite pattern suggests that two opposing forces are at play when shaping the relationship between WFH and GDP per capita. However, interpersonal interactions can be completed from home when mediated by ICT. As seen in Figure 2, countries from the PIAAC dataset that have jobs more intensive in Interpersonal interaction tasks (high value of the Interpersonal interactions index) also tend to be more intensive in the use of ICT at work (low value of the Low ICT at work index). This is the case

11 Because the LMPS dataset only includes three countries, we do not present correlations for this sample.

12 The negative (positive) association between GDP per capita and the Physical/Manual (Interpersonal interactions) index is stronger economically and statistically when using the sample of PIAAC countries in comparison to STEP countries.

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of countries such as the United States and Singapore as opposed to countries such as Lithuania or Kazakhstan (Figure 2, panel [a]); that is, several of the tasks embedded in such jobs are more prone to be performed remotely. In other words, ICT use at work would tend to weaken the effect of Interpersonal interactions intensity on WFH measures. For STEP countries, we do not find an association between the Interpersonal interactions and ICT use at work indexes. In this group of countries, where the development level is lower in comparison to PIAAC countries, use of ICT at work is not expected to counteract the effect of Interpersonal interaction tasks on WFH. The negative correlation between Interpersonal interaction tasks and Low ICT use at work in the PIAAC dataset can also be observed within countries (see Figure A1 in the Appendix).

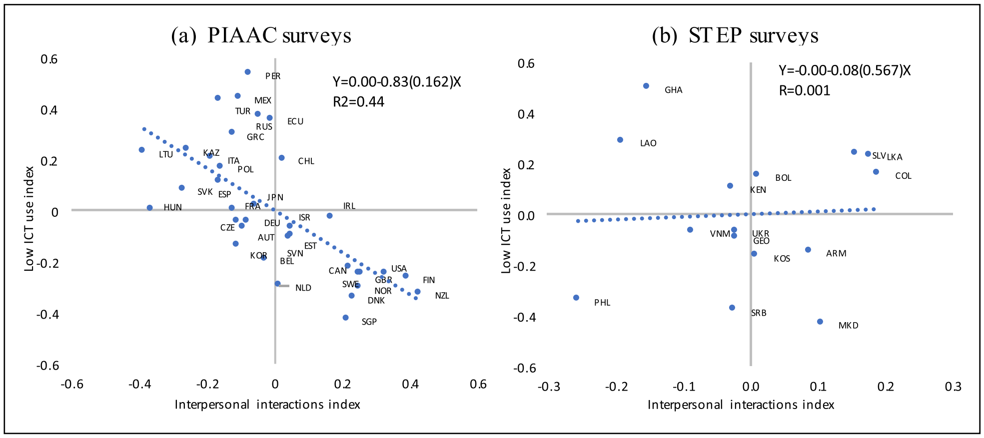

Figure 2 ICT use at work and Interpersonal interactions intensity across countries.

Source: Own elaboration based on STEP and PIAAC surveys.

Notes: The vertical axis measures the Low ICT use at work index (a higher value means lower ICT use at work), while the horizontal axis measures the Interpersonal interactions index (a higher value means more intense interpersonal interaction tasks). 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—that is, countries in which people use more ICT at work also have higher internet connectivity at home—there are some differences, particularly among less-developed countries.[13] 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 (Figure 3, panel [a]). 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, panel [b]). Thereby, while certain jobs could be amenable to telecommuting based on the task measures, poor internet connectivity implies that many workers may not be able to do their jobs at home.

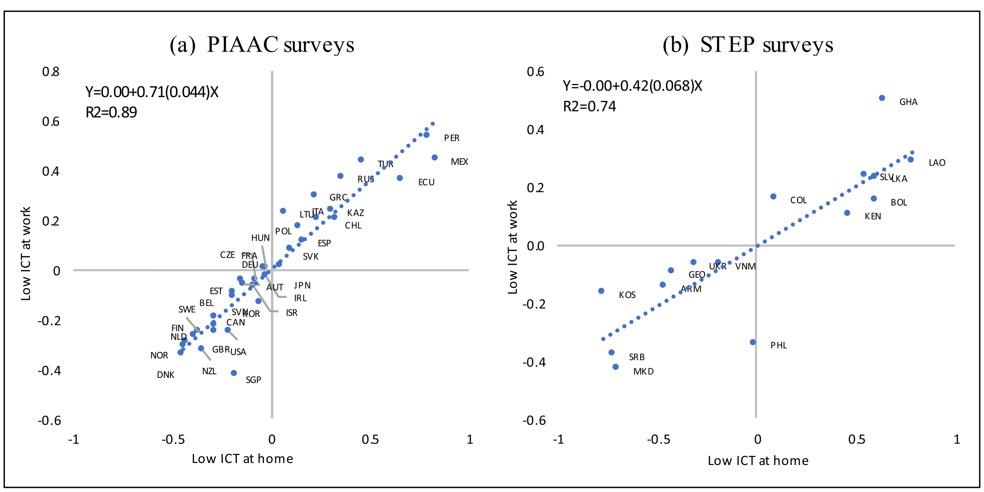

Figure 3 ICT use at work and at home across countries.

Source: Own elaboration based on STEP and PIAAC surveys.

Notes: The vertical axis measures the Low ICT use at work 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, therefore we consider households having internet access at home if they have a computer and fixed telephone access.

13 While El Salvador emerges as an outlier, this status 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.

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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 Latin America and Caribbean region. In the STEP sample, countries from the Europe and Central Asia region have jobs more amenable to working from home, while the opposite is true for Sri Lanka, El Salvador, Ghana, and Lao PDR. In the LMPS sample, Jordan has jobs more amenable to WFH in comparison to Tunisia and Egypt. In contrast to Dingel and Neiman (2020), 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.

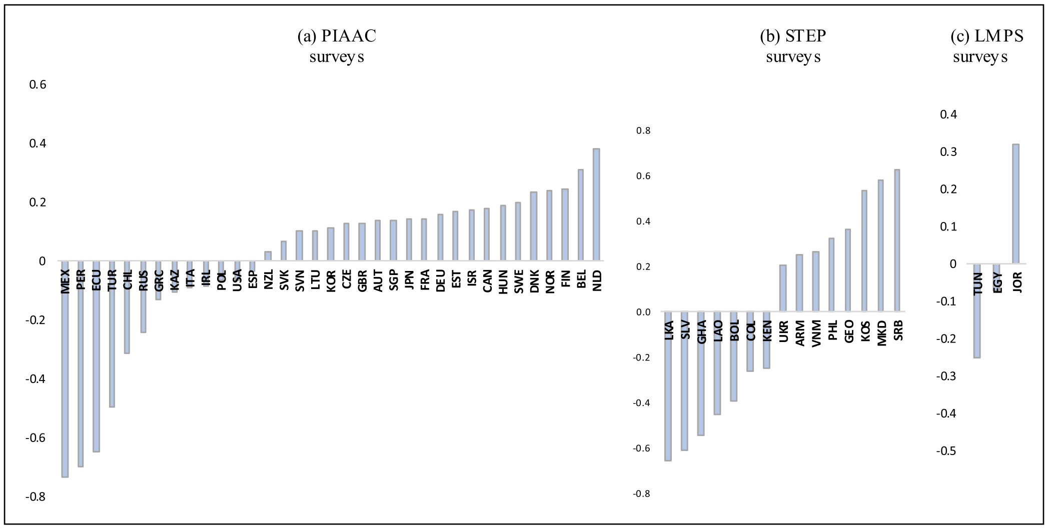

Figure 4 WFH amenability measure across countries.

Source: Own elaboration based on PIAAC, STEP, and LMPS surveys.

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

The difference between our results and those of Dingel and Neiman (2020) 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 the Appendix 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) (Panel [b] of the Figure). If we imputed the U.S. WFH measures to each occupation of these other two countries (as in Dingel and Neiman (2020)), 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 (Panel [a] of the Figure). For example, the US WFH measure 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, as 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 occupational level. A simple decomposition shows that less than one third of the variation in the WFH measure is explained by variation between 3-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 (Figure 5). For example, the average job in the Netherlands is 0.38 standard deviations above the average job in PIAAC countries in terms of its amenability to working from home, while Ecuador and Turkey are 0.65 and 0.5 standard

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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.

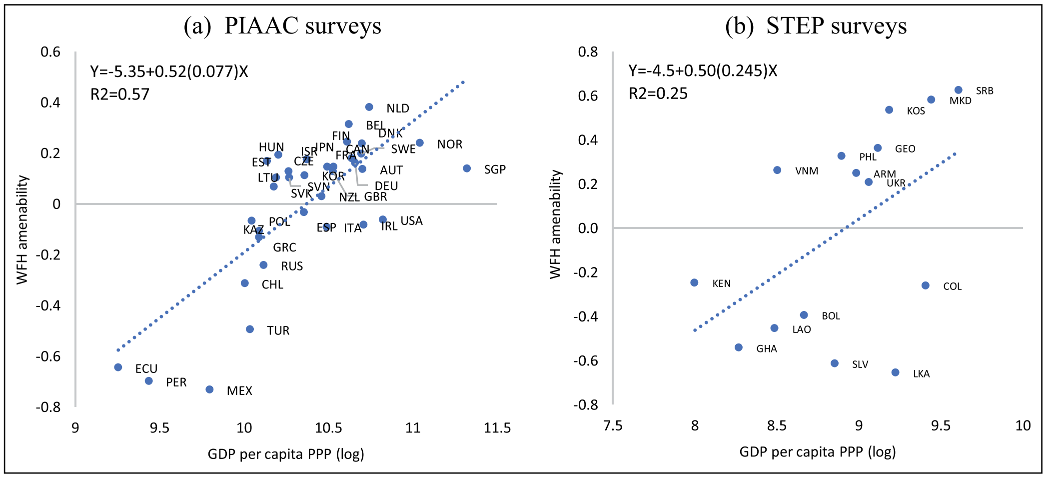

Figure 5 WFH amenability measure and GDP per capita.

Source: Own elaboration based on STEP and PIAAC surveys and WDI.

Notes: The vertical axis measures WFH amenability in standard deviations from the mean of the PIAAC/ STEP samples. A higher value indicates that jobs are more amenable to WFH.

3.2 WITHIN-COUNTRY FINDINGS

Within countries, large disparities exist in terms of jobs' amenability to working from home. Figure 6 shows differences with respect to the average job for the whole PIAAC, STEP, and LMPS data sets.[14] Across most countries, women are more likely to have jobs more amenable to WFH because they are less likely to have jobs intensive in physical/manual work than men. Educational attainment is strongly linked to WFH amenability, as 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 due to a combination of counteracting forces. On the one hand, the interpersonal interactions intensity increases and ICT use declines with age, which tends to reduce the amenability of older workers' jobs 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 interpersonal interactions 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 interpersonal interactions. 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 because informal workers have more physical/manual-intensive jobs and lower ICT use at work. This situation was very important during the COVID-19 crisis because informal workers are less likely to be protected against important risks and subsidies and other forms of assistance are easier to implement when using the social insurance infrastructure, which often only includes formal workers.

The sectors that emerge as more amenable to WFH tend to be the same across most countries in the PIAAC and LMPS data sets.[15] 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.

14 Tables showing country-level findings are available in the Supplementary materials.

15 STEP surveys only allow separation between four economic sectors (agriculture, industry, commerce, and other services).

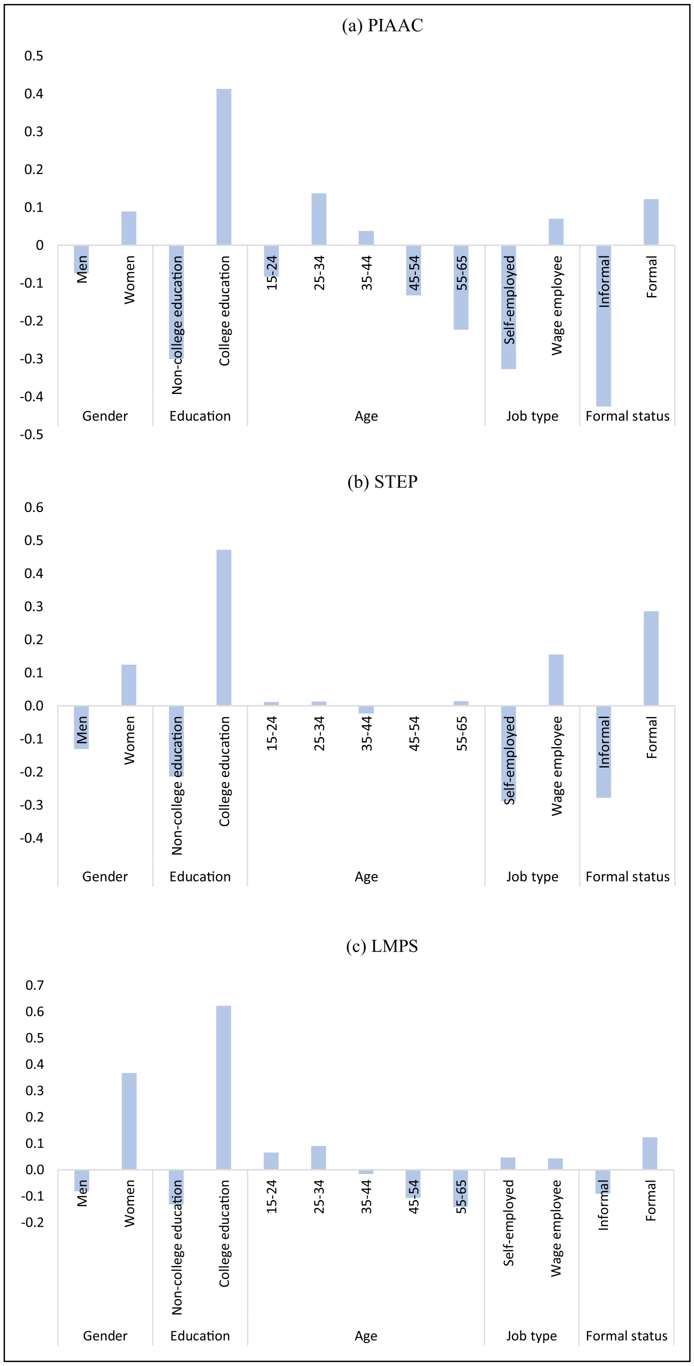

Figure 6 WFH amenability measure, by individual characteristics.

Source: Own elaboration based on PIAAC, STEP, and LMPS surveys.

Notes: The vertical axis measures WFH amenability 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.

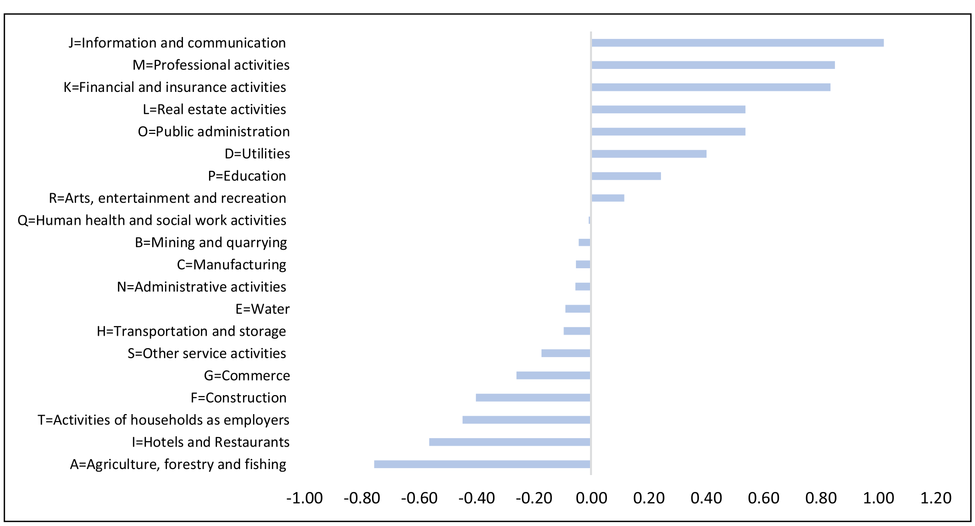

Figure 7 WFH amenability measure by sector of economic activity, PIAAC sample.

Source: Own elaboration based on PIAAC surveys.

Notes: The horizontal axis measures WFH amenability in standard deviations from the mean of the PIAAC sample. A higher value indicates that jobs are more amenable to WFH.

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Finally, we regress the WFH amenability measure for each data set on individual and job characteristics and confirm that 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 (Column 1 of Table 3).[16] Differences in educational attainment predict large gaps in WFH measures: the jobs of college graduates are 0.70 standard deviation more amenable to WFH than those of their less educated counterparts in the PIAAC sample. These figures for the STEP and LMPS samples are 0.51 and 0.61, respectively. In STEP and LMPS countries, 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. These patterns also appear within occupations and sectors (Column 2 of Table 3),[17] reinforcing our previous result—that is, most of the variation in the WFH measure takes place within occupations—and highlighting the importance of using information on tasks performed at work at the individual level when measuring work from home amenability.

Table 3 OLS regression of the WFH amenability measure.

DEPENDENT VARIABLE:	WFH AMENABILITY MEASURE					
	PIAAC		STEP		LM PS	
	(1)	(2)	(1)	(2)	(1)	(2)
Women	0.0611	0.0254	0.251	0.196	0.38	0.294
	[0.00613]***	[0.00612]***	[0.0116]***	[0.0116]***	[0.0167]***	[0.0174]***
College education	0.702	0.294	0.509	0.288	0.615	0.313
	[0.00642]***	[0.00716]***	[0.0137]***	[0.0158]***	[0.0173]***	[0.0229]***
25–34	0.305	0.39	−0.154	−0.145	−0.0788	−0.119
	[0.0141]***	[0.0129]***	[0.0192]***	[0.0185]***	[0.0213]***	[0.0207]***
35–44	0.302	0.283	−0.199	−0.171	−0.144	−0.192
	[0.0121]***	[0.0109]***	[0.0197]***	[0.0191]***	[0.0215]***	[0.0210]***
45–54	0.224	0.204	−0.222	−0.187	−0.162	−0.241
	[0.0119]***	[0.0107]***	[0.0202]***	[0.0196]***	[0.0229]***	[0.0224]***
55–65	0.0747	0.074	−0.202	−0.175	−0.139	−0.211
	[0.0122]***	[0.0109]***	[0.0226]***	[0.0220]***	[0.0292]***	[0.0285]***
Wage employee	0.204	0.11	0.115	0.00590	0.0471	0.00378
	[0.00870]***	[0.00823]***	[0.0134]***	[0.0141]***	[0.0155]***	[0.0170]
Constant	−1.045	−1.016	−0.196	0.0292	−0.297	0.547
	[0.0264]***	[0.0466]***	[0.0198]***	[0.0448]***	[0.0240]***	[0.156]***
Occupation and sector FE	No	Yes	No	Yes	No	Yes
Observations	138,954	138,954	22,473	22,473	22,088	22,088
R-squared	0.21	0.391	0.279	0.327	0.148	0.208

Source: Own elaboration based on STEP, PIAAC and LMPS surveys.

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

16 Tables showing country-level regression results are available in the Supplementary materials.

17 An exception is the lack of statistical significance of the variable indicating whether a worker is a wage employee for the STEP and LMPS samples.

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4. VALIDATION

4.1 HOW WELL DOES WFH AMENABILITY PREDICT JOB LOSSES?

Workers with higher WFH amenability were probably in a better position to keep their jobs when social distancing measures were in place during the pandemic, while workers with lower chances of moving their working activities from the usual workplace to home faced higher job loss risks. We evaluate how our WFH measure correlates with observed employment changes between 2019 and 2020 using longitudinal data from the Encuesta Nacional de Empleo (ENE) in Chile.

Using the panel structure of ENE, we create three panels of individuals where, for each person, the first observation corresponds to a pre-pandemic quarter—Q2, Q3, or Q4 of 2019—and the second observation corresponds to the same quarter one year after, that is, when the pandemic was in place—Q2, Q3, or Q4 of 2020.[18] We focus on persons ages 16–64 who were employed pre-pandemic (in 2019), and we assess whether they lost their jobs in 2020. For each worker in the ENE sample, we predict a WFH value using the procedure applied in Gottlieb et al. (2021a): we use the estimated coefficients from a model where our WFH measure is the outcome and the explanatory variables are indicators of gender, age groups, education level, wage employment, and 1-digit occupations. This model is estimated by OLS using Chilean PIAAC data and survey weights.

Our results appear in Table 4 and show that a higher WFH amenability helped insulated Chilean workers from job losses. An increase of one standard deviation in the WFH (predicted) measure is associated with a reduction of 11.3 percentage points in the likelihood of losing the job (column 1). A similar coefficient is obtained when controlling for an indicator of whether the person worked (pre-pandemic) in an essential sector (column 2).[19] The interaction term between the WFH (predicted) measure and the indicator of working in an essential industry is not statistically significant, indicating that the employment protection obtained through WFH amenability was not different when comparing essential and non-essential sectors (column 3).[20] Our main finding—the negative association between WFH and the probability of job loss—is consistent with evidence presented using other WFH measures (for instance, Garrote Sanchez et al. 2021; Mongey, Pilossoph, and Weinberg 2021; Gottlieb et al. 2021b; Adams-Prassl et al. 2020; Montenovo et al. 2020; Cajner et al. 2020).

Table 4 WFH and probability of job loss.

Sources: Own elaboration using Encuesta Nacional de Empleo (ENE) from Chile and Chilean PIAAC data.

Notes: All models include quarter fixed effects and use survey weights. WFH predicted measure obtained from a model whereby the WFH measure is regressed on indicator variables of gender, age groups, education, wage employment, and 1-digit occupations using PIAAC data from Chile. The estimated coefficients are then imputed to the ENE sample. ENE sample comprises workers ages 16–64 who were employed in 2019. Essential sectors defined following the guidelines of the Ministerio de Economia, Fomento y Turismo of Chile. Robust standard errors in brackets. *** p < 0.01, ** p < 0.05, * p < 0.1

DEPENDENT VARIABLE:	=1 IF LOST THE JOB		
WFH (predicted)	–0.113	–0.110	–0.106
	[0.00879]***	[0.00882]***	[0.0106]***
=1 if employed in an essential sector		–0.0360	–0.0404
		[0.0123]***	[0.0129]***
WFH (predicted)* =1 if employed in an essential sector			–0.0145
			[0.0190]
Constant	0.214	0.225	0.226
	[0.0120]***	[0.0128]***	[0.0130]***
Observations	11,722	11,722	11,722
R-squared	0.031	0.033	0.033

18 The ENE follows a rotating design whereby a household is interviewed in a given month, leaves the sample for the next two months, and is interviewed again in the next two months. This sequence is repeated six times.

19 Essential sectors continue their normal operations during the lockdown period.

20 This result is similar to the finding of Gottlieb et al. (2021b) for Peru.

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4.2 HOW WELL DOES WFH AMENABILITY PREDICT OBSERVED WFH?

The ENE of Chile contains information on the place of work in the last week, allowing us to know whether a person worked from home. Using the sample of people ages 16–64 who were employed in Q2, Q3, or Q4 of 2020, we compare the predicted WFH measure (using the same procedure as in the previous subsection) with a variable taking the value 1 if the person worked from home in the previous week, and 0 otherwise. The share of workers who were working from home in Chile during the pandemic quarters of 2020 was 21.9%.

The comparison is presented in a binned scatter plot in which the predicted WFH measure is divided into 20 groups of equal size and the mean value within each group compared to the mean value of the binary variable that indicates whether a worker worked from home in the previous week. Figure 8 shows a positive correlation between the predicted WFH measure and the share of workers who worked from home between Q2 and Q4 of 2020. This finding adds to previous evidence using other WFH measures (Mongey, Pilossoph, and Weinberg 2021; Gottlieb et al. 2021a).

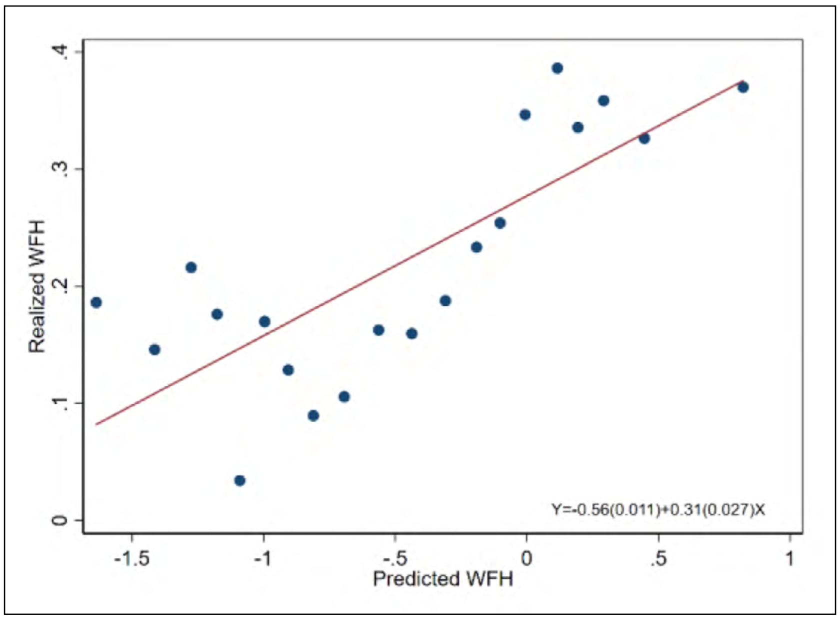

Figure 8 Predicted and Observed WFH.

Sources: Own elaboration using Encuesta Nacional de Empleo (ENE) from Chile and Chilean PIAAC data.

Notes: Predicted WFH measure obtained from a model where the WFH measure is regressed on indicator variables of gender, age groups, education, wage employment, 1-digit occupation, and sectors using PIAAC data from Chile. The estimated coefficients are then imputed to the ENE sample. ENE sample comprises workers ages 16–64 who were employed in 2020. N = 9,629.

5. HOW DOES WFH AMENABILITY COMPARE TO BINARY MEASURES?

This section proposes two types of comparisons between our WFH amenability measure and one that applies the binary approach. First, we compare our standardized WFH measure to the share of jobs that can be done from home in each country. To construct this share, we follow a methodology similar to that of Dingel and Neiman (2020), assuming that only one condition must be satisfied for a job not to be amenable to WFH. In particular, we restrict the set of task variables to those closer to the ones used by Dingel and Neiman (2020). For the PIAAC sample, we define a worker who cannot work from home as one for whom 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. For the STEP sample, we follow Saltiel (2020) and consider that a worker cannot work from home if at least one of the following conditions is met: (i) not using a computer, (ii) lifting anything heavier than 50 pounds, (iii) repairing/maintaining electronic equipment, (iv) operating heavy machinery or industrial equipment, (v) reporting that contact with customers is very important.

The results in Figure 9 show that the estimated share of workers who can WFH (binary approach) is positively and highly correlated with our (standardized) measure for both the PIAAC and STEP samples. Panel (a) for the PIAAC sample indicates that the share of jobs that can be done from home ranges from around 7% in Mexico and Ecuador to more than 36% in Finland and the Netherlands. The results for the STEP sample in panel (c) show that the share ranges from

5% in Ghana to 34% in the Philippines. The correlations presented in the figure indicate that the standardized WFH measure in the average job among all PIAAC (STEP) countries (standardized WFH measure equal to zero) corresponds to a 24% (16%) WFH likelihood using the binary measure previously employed in the literature.

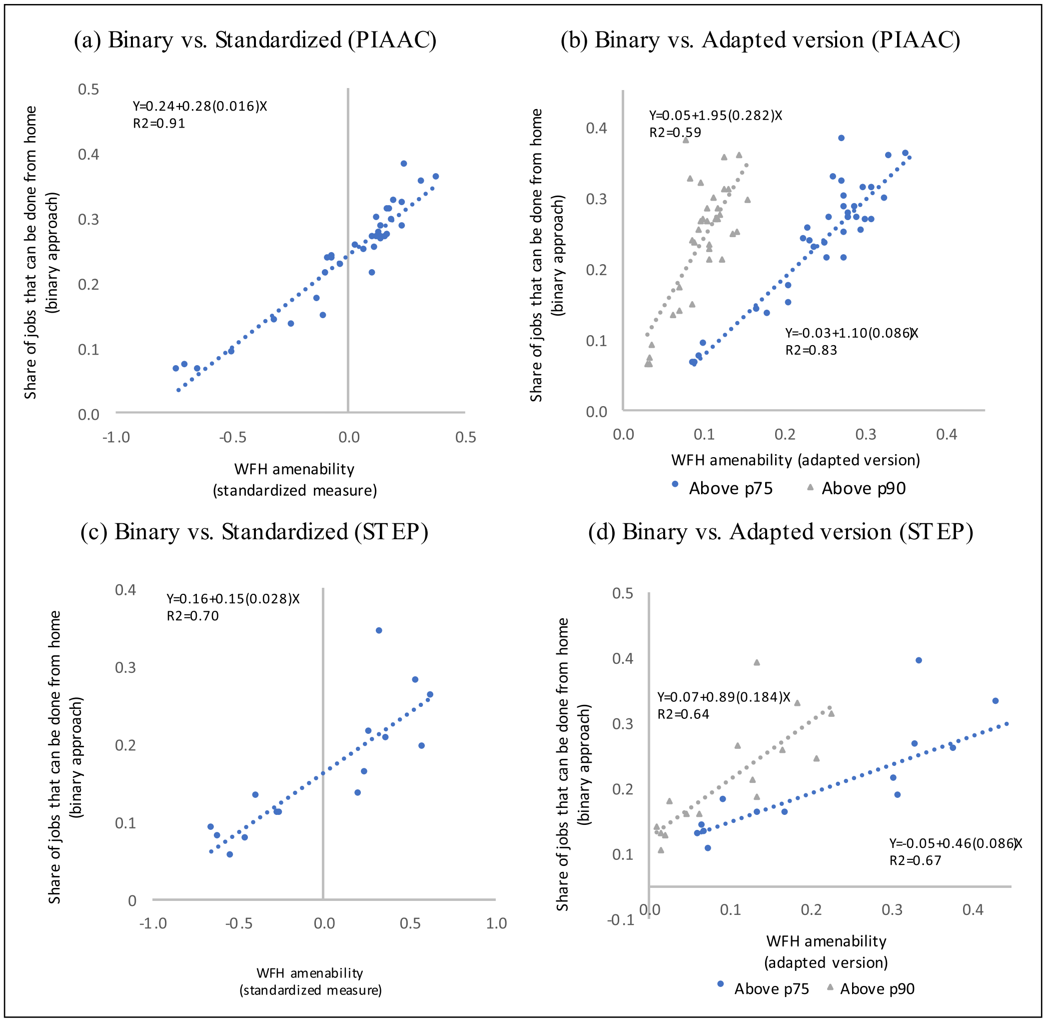

Figure 9 Comparison between WFH measures.

Sources: Own elaboration based on PIAAC and STEP.

Second, we compare the share of jobs that can be done from home (binary approach) to an adapted version of our WFH measure whereby we calculate the share of jobs that are at the top of the PIAAC or STEP WFH distributions in each country—for instance, above the 75th or 90th percentiles.[21] These are the jobs that have high amenability to WFH. The advantage of this adapted version is that the outcome is directly comparable to measures based on the binary approach. Results in panels (b) and (d) show a positive correlation between the adapted version of our WFH measure and the one that comes from implementing the binary approach. The correlation is higher when the adapted measure captures the percentage of jobs above the 75th percentile of the PIAAC/STEP WFH distributions.

These results indicate that measures based on different methodologies (binary approach and standardized approach) are capturing the same phenomenon—that is, positive and high correlations in panels (a) and (c) of Figure 9—and that adapting our measure to show the percentage of jobs that in each country are more amenable to working from home can be informative especially considering that it is easier to communicate in a policy-relevant manner. However, the standardized measure contains more information than the binary one, a feature that could be useful in empirical studies that require more variation in the WFH variable.

21 The same limitations discussed before for our standardized WFH measure apply for the adapted version. In particular, the share of jobs at the top of the WFH distribution is comparable across PIAAC or STEP countries, but not across surveys.

6. CONCLUDING REMARKS

This paper provides new evidence on which countries and types of workers have jobs that are more 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, this paper proposes a measure of jobs' amenability to WFH (instead of defining whether a job can or cannot be done from home) including internet access at home as one of the determinants of WFH possibilities.

The findings show that poorer countries and workers who are male, with lower levels of education, self-employed, and informal are employed in jobs less amenable to working from home. Additionally, the analysis provides evidence on the WFH amenability measure as a predictor of actual job losses and on its positive correlation with the observed share of workers who work from home.

Our findings highlight the importance of accelerating ICT adoption to facilitate home-based work when working on location is not an option and also considering that WFH can become a common work arrangement after the pandemic ends. The results show that some of the less-developed countries have jobs that could be amenable to being performed from home according to the task measures, but lack of internet access could limit this possibility.

Acceleration of ICT adoption could not be enough and may need to be accompanied by training policies. Our measure informs about the technical possibilities of performing a job from home, but some workers may be less productive when working from home compared to their productivity in the usual workplace due to low levels of certain skills that help successfully perform a job remotely—for instance, organization, or adaptability.

The results also show that using individual information about the tasks that people do at work is important, as occupations capture less than one third of the types of tasks that workers do on the job. All these results are important not only to understand the labor market's effects of the pandemic, but also from a long-term perspective as working from home is expected to continue after the pandemic is over.

ADDITIONAL FILE

The additional file for this article can be found as follows:

- **Appendix.** Tables A1–A2 and Figures A1–A2. DOI: https://doi.org/10.31389/eco.8.s1

AUTHOR NOTE

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 "Jobs Undone: Reshaping the Role of Governments toward Markets and Workers in the Middle East and North Africa" of the World Bank MNA Chief Economist Office.

COMPETING INTERESTS

The authors have no competing interests to declare.

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