Working from Home in Developing Countries*

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Abstract

We examine workers' ability to work from home, as well as their propensity to actually work from home in developing countries. We use worker-level STEP data covering the task content of jobs to measure the ability to work from home. While the ability to WFH is low in developing countries, it exhibits significant heterogeneity across and within occupations and worker characteristics. Patterns of actual work from home in data from Brazil and Costa Rica align closely with those predicted based on STEP data, in terms of both overall levels and variation with occupation and individual characteristics.

Keywords: COVID-19, Occupations, Tasks, Work from home, Remote Work.

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1 Introduction

The spread of Covid-19 has led to the widespread adoption of social distancing in countries across the world, be it in response to government mandates or on a voluntary basis. Since social distancing frequently involves the closure of workplaces to limit interpersonal contact, the ability to work from home (WFH) is a key factor for determining the economic consequences of social distancing. Various papers have measured WFH ability in developed countries (Dingel and Neiman, 2020; Adams-Prassl et al., 2020a,b; Bick et al., 2020; Boeri et al., 2020; del Rio-Chanona et al., 2020; Fadinger et al., 2020; Alipour et al., 2020; Hensvik et al., 2020; Mongey and Weinberg, 2020), finding that around 40% of jobs could potentially be carried out from home. However, these measures cannot be directly extrapolated to developing countries, as the task content of occupations may vary significantly across contexts (Dicarlo et al., 2016; Lo Bello et al., 2019). Yet, understanding the potential to WFH in these countries is of critical importance, as low-income countries also see extensive adoption of social distancing.[1]

In this paper, we measure the ability to work from home in developing countries, and also present evidence on who is actually working from home during the pandemic. We first take advantage of worker-level data on task content from the Skills Toward Employability and Productivity (STEP) survey, which covers 17,000 workers in urban areas across ten low- and middle-income countries. We follow Dingel and Neiman (2020) and build a WFH measure in developing countries based on a task-exclusion approach. STEP includes detailed information on workers' occupations, self-employment status, educational attainment and gender. Since task content is measured at the worker-level in STEP, we can examine variation in workers' ability to work from home both across occupations and across demographic groups. Second, we rely on labor force surveys conducted in Brazil and Costa Rica during the pandemic, which measured the prevalence of actual work from home in the second quarter of 2020. Since these data sources include detailed information on workers' employment outcomes along with their observed characteristics, we again document heterogeneity in the prevalence of actual WFH across occupations as well as education and gender groups. Predicted WFH patterns computed using worker characteristics and our estimates from STEP data closely proxy actual WFH patterns in these countries.

Our preferred WFH measure rules out working from home if a worker's job involves tasks that arguably make it impossible to exercise the job from home. These job tasks include repairing electronic equipment, operating heavy machinery, reporting that customer interaction is very important, reporting a physically demanding job or *not* using e-mail at work. According to this measure, only 9.3% of workers in the full STEP sample can work from home. While this estimated aggregate WFH share is relatively low, there is substantial heterogeneity across occupations, as the estimated share of workers in elementary jobs who can WFH equals 1.3%, while it reaches 23.8% for managers. We also find differences in predicted WFH across workers' observed characteristics, as

[1]Twenty-two low- and lower-middle income countries have implemented lockdowns with a stringency index above 80 (corresponding to the 75th percentile of the world distribution) (Hale et al., 2020). Reductions in mobility are also similar in many countries; e.g. Figure A1 shows similar patterns in Brazil, Costa Rica, and the United States.

more educated workers, wage employees, females, and wealthier workers are more likely to be able to work from home. These groups remain more likely to be able to WFH even within three-digit occupations. A variance decomposition exercise shows that the contribution of country fixed effects to the variance of predicted WFH is minor, indicating that our measure can be extrapolated to countries within the income range covered by STEP countries. Finally, the ability to WFH implied by STEP data is lower than that found in O*NET data from the US in almost all occupations.[2]

We examine the drivers of actual WFH during the pandemic using labor force surveys conducted in Brazil and Costa Rica in the second quarter of 2020. In Brazil, we observe whether individuals are working from home during the pandemic, and the Costa Rica survey captures whether individuals are teleworking.[3] The estimated share of workers who are working from home equals just 10.6% in Costa Rica and 13.3% in Brazil, far below the corresponding shares in developed countries. These averages hide important differences in the likelihood of working from home across occupations, as the estimated WFH share for plant operators is below 1% in both countries, while it exceeds 40% for professionals.[4] We further find a higher prevalence of actual WFH for more educated workers, women, and wage employees, in line with our measure of work from home ability. To validate our esimates from STEP data, we impute a predicted WFH score for each worker in the Brazil and Costa Rica surveys based on their occupations and observed characteristics and our estimates from STEP. We document a strong association between predicted and observed WFH in these two countries. This gives us confidence in the transferability of our estimates from STEP to other countries in the same broad income range.

This paper makes several contributions to the nascent literature on workers' ability to work from home. It extends Saltiel (2020), who was the first to present evidence on the determinants of WFH in developing countries.[5] It fits closely with a number of papers measuring the feasibility of working from home in developed economies (Dingel and Neiman, 2020; Adams-Prassl et al., 2020a,b; Bick et al., 2020; Boeri et al., 2020; del Rio-Chanona et al., 2020; Fadinger et al., 2020; Alipour et al., 2020; Hensvik et al., 2020; Mongey and Weinberg, 2020). Like Adams-Prassl et al. (2020b), our analysis goes beyond heterogeneity across occupations, as we document the importance of within-occupation heterogeneity in workers' abilities to work from home. The paper thus also contributes to a broader literature examining within-occupation differences in task content (Autor and Handel, 2013; Stinebrickner et al., 2019).

To the best of our knowledge, ours is the first paper to examine patterns in actual work from home in developing countries. Importantly, this information allows us to validate our measure of WFH ability using information on workers' occupations and characteristics. Our validation extends

[2]Since our WFH measure relies on task questions which are also available in O*NET, we can compute an alternative, O*NET-based measure of WFH. Across almost all three-digit occupations, the O*NET-based measure predicts substantially higher WFH than our STEP-based measure. This result can be explained by differential task content within occupations in developed vis-à-vis developing countries (Lewandowski et al., 2019).

[3]For comparability with STEP, we focus on urban respondents in both countries.

[4]In Costa Rica, the estimated prevalence of WFH at the three-digit occupation level is strikingly similar to our predicted shares using STEP data.

[5]Hatayama et al. (2020) and Garrote Sanchez et al. (2020) have more recently provided related evidence on this issue. However, the data they use do not allow measuring actual work from home.

Dingel and Neiman (2020) and Bick et al. (2020), who validated their measure of WFH ability using cross-country and industry-level variation in the prevalence of WFH, respectively.

The rest of the paper proceeds as follows. In Section 2, we present our worker-level measure of WFH in developing countries and examine heterogeneity across occupations and observed characteristics. In Section 3, we present evidence on the prevalence of WFH in Brazil and Costa Rica. We compare our WFH measure to workers' actual likelihood of working from home in these two countries. In Section 4, we discuss the results and conclude.

2 Who Can Work from Home in Developing Countries?

2.1 Data Sources

To measure the feasibility of working from home, we use data from the first two rounds of the STEP household survey, covering workers in urban areas across ten countries in 2012-2013, including Armenia, Bolivia, China (Yunnan Province), Colombia, Georgia, Ghana, Kenya, Laos, Macedonia and Vietnam. STEP surveys are representative of the working age (15-64 year old) population in urban areas across these countries. We use data on the main respondent, for whom we observe age, gender and educational attainment, along with information on labor market outcomes, including current employment status and whether they have worked in the past twelve months.[6] Furthermore, we observe whether they work as wage employees, in self-employment or in unpaid family work.[7] STEP also includes workers' occupations under the harmonized ISCO-08 classification.

Finally, STEP also contains information on the tasks that respondents perform at work. Since all STEP country surveys include the same task content questions, the analysis is directly comparable across countries. Moreover, since information on tasks is gathered at the worker level, we can examine how workers' capacity to work from home varies not just with occupation, but also with other individual characteristics.

2.2 Work from Home Definition

Our approach to measuring the feasibility of working from home follows Dingel and Neiman (2020) in aiming to capture whether workers could potentially work from home, and not whether they have done so in the past.[8] STEP data allow us to construct a WFH measure across a wide range of countries by leveraging comparable worker-level data on job task content. We consider task measures which are informative of the physical and social nature of the job, along with information on technology use which may be carried out from home. Our preferred definition rules out working from home if a worker performs any of the following tasks at work: repairing/maintaining electronic equipment, operating heavy machinery or industrial equipment, reporting they have a physically

[6]Since STEP also includes information on household assets, we classify respondents by their quintile ranking in the within-country asset index distribution as a measure of their capacity to cope with the shock.

[7]We restrict the analysis to respondents who have been employed in the past twelve months. We further drop individuals in unpaid family work or in the armed forces.

[8]STEP does not include questions asking respondents whether they have previously worked from home.

demanding job, reporting that contact with customers is very important, or *not* using e-mail at work.

2.3 Empirical Evidence

In the first column of Table 1, we present average WFH feasibility in the STEP sample. We include sample weights to represent the working-age population of 15-64 year olds in each country, and all countries are weighted equally. Overall, 9.3% of urban employment could be done remotely in the ten STEP countries.[9,10] The feasibility of WFH varies strongly across broad occupation groups. While close to one-quarter of jobs in managerial, professional occupations and clerical support occupations could be done from home, fewer than 3% of jobs in elementary occupations, crafts, or occupations involving plant or machine operation can be done remotely. In Table A1, we show that similar results emerge in predicted WFH ability across the ten countries in the sample.

WFH ability varies not only at the occupation level, but also across personal and job characteristics. In the second and third columns of Table 1, we show that educational attainment is a strong predictor of the ability to work from home, as the estimated share for high school completers surpasses that of dropouts by 13 percentage points. High school graduates have higher estimated WFH than their dropout counterparts across all occupations, and these differences are significant across all but two broad occupation groups. Similarly, the ability to WFH for wage employees (12.4%) is far higher than that for self-employed workers (3.3%).[11] These differences are particularly salient among individuals in high-paying managerial or professional occupations. In the first two panels of Figure A2, we show that wage employees and high school completers have high relative likelihoods of being able to work from home in all STEP countries. Lastly, women have a slightly higher predicted ability to WFH than men, with statistically significant differences emerging among managers, professionals, clerical support workers and services/sales workers.

In the last panel of Figure A2, we show heterogeneity in WFH ability across the within-country asset index distribution. The sample average shows that just 3.3% of households in the bottom quintile can work from home, far trailing their wealthier peers in the top quintile at 17.3%. As such, workers with limited access to self-insurance are far less likely to be able to work from home in developing countries.

These results illustrate the importance of measuring task content at the worker-level (see also Adams-Prassl et al., 2020b). This is an important advantage of the STEP data, in contrast to e.g. O*NET, which only allows for occupation-based measures (see below for a further comparison to

[9] Internet access has grown significantly in developing countries since STEP surveys were carried out in 2012-13 (https://data.worldbank.org/indicator/IT.NET.USER.ZS). By ruling out WFH for workers who do not use e-mail, we may thus be underestimating the share of WFH in these countries. We address this concern by replacing the e-mail exclusion with a 'computer-use-at-work' exclusion, which captures jobs which required computers back in 2012-13 but may have incorporated e-mail use since. This alternative measure indicates that 12.9% of jobs in STEP could be done from home, remaining far below the developed country shares.

[10] STEP contains information on urban residents. WFH ability in rural areas depends critically on the ability to WFH in the agricultural sector. See Gottlieb et al. (2020) for a discussion.

[11] We also find large differences across workers' formal employment status, as 16.1% of formal workers are able to WFH, compared to just 4.7% of their informal counterparts.

O*NET).

Table 1: Predicted WFH by Occupations and Characteristics in STEP

		Educational Attainment		Self-Employment		Gender	
	Full Sample	HS Graduate	HS Dropout	Wage Employee	Self-Employed	Female	Male
One-Digit Occupation	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Managers	0.238	0.258	0.084***	0.301	0.160***	0.233	0.242
Professionals	0.196	0.202	0.099***	0.201	0.154*	0.193	0.203
Technicians and Associate Professionals	0.200	0.222	0.082***	0.214	0.101***	0.215	0.186
Clerical Support Workers	0.282	0.315	0.128***	0.286	0.176*	0.326	0.205***
Services and Sales Workers	0.030	0.054	0.009***	0.045	0.017***	0.027	0.036
Skilled Agricultural, Forestry and Fishery Workers	0.001	0.005	0.000	0.003	0.000	0.000	0.001
Craft and Related Trades Workers	0.012	0.022	0.004***	0.011	0.012	0.010	0.013
Plant and Machine Operators, and Assemblers	0.007	0.014	0.000	0.009	0.003	0.007	0.008
Elementary Occupations	0.013	0.040	0.001***	0.014	0.011	0.018	0.008*
Sample Average	0.093	0.148	0.014***	0.124	0.033***	0.100	0.084***
Observations	17,592	10,090	7,502	11,095	6,497	9,349	8,243

Source: Skills Toward Employability and Productivity (STEP) Survey. Note: Table 1 documents the share of workers who can work from home by one-digit occupation, educational attainment, self-employment and gender. Results are weighted using sample weights to represent the working-age population of 15-64 year olds in each STEP country. We estimate a test of equality of WFH means across educational attainment, self-employment and gender and present the relevant standard errors in columns (3), (5) and (7), respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The evidence presented so far shows that both occupations and workers' characteristics are important determinants of WFH ability. To further understand the contribution of different factors to differences in the capacity to work from home, we estimate the following regression:

$$WFH_{ioc} = \beta \boldsymbol{X}_i + \gamma_o + \lambda_c + \varepsilon_{ioc} \tag{1}$$

where $\boldsymbol{X}_i$ represents a vector of worker i's observed characteristics, including educational attainment (in years), age, gender and self-employment status; γ_o captures one- or three-digit occupational fixed effects and λ_c denotes country fixed effects. We present the estimated results of equation (1) in Table 2. The first column shows that higher-educated workers, wage employees and women are more likely to be able to work from home. In the second column, we control for one-digit occupations, finding that the sign of the estimated coefficients remains the same —with varying statistical significance, echoing the bivariate patterns reported in Table 1. Importantly, in the last column, we still find that workers' observed characteristics play an important role in driving the prevalence of WFH even within narrowly defined three-digit occupations. We thus remark the importance of using worker-level task content data for measuring the ability to work from home in developing countries.

2.4 Cross-Country Heterogeneity

While we have so far focused on sample averages, STEP covers a wide range of countries across the development spectrum — their GDP per capita (PPP) ranges from \$3,000 to upwards of \$14,000. At the same time, in Figure A3, we document important cross-country heterogeneity in WFH ability — ranging from 3.2% in Ghana to 15.4% in Georgia — which is strongly correlated with

Table 2: Determinants of working from home: observables and occupations

	(1)	(2)	(3)
Educational Attainment	0.015***	0.008**	0.007***
	(0.003)	(0.003)	(0.002)
Age	-0.000	-0.001**	-0.000*
	(0.000)	(0.000)	(0.000)
Male	-0.025*	-0.015	-0.024*
	(0.012)	(0.012)	(0.013)
Wage Employment	0.036**	0.017	0.023**
	(0.012)	(0.010)	(0.007)
Observations	17592	17592	17591
R^2	0.083	0.137	0.202
Occupation FE	None	One-Digit	Three-Digit

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Standard errors in parentheses. Table 2 presents the estimated coefficients from equation (1) across different specifications. The first column does not include occupation fixed effects, whereas the second and third columns include one- and three- digit occupation fixed effects, respectively. Results are weighted using sample weights to represent the working-age population of 15-64 year olds in the sample. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

countries' income per capita. The income elasticity of the share of jobs which can be done from home equals 0.046.

To assess whether cross-country differences in WFH can be explained by variation in countries' occupational structure and workers' observables, we conduct a variance decomposition exercise following the estimated coefficients from equation (1). We present the results in Table A2. Workers' characteristics on their own account for 2% of the variance in the WFH measure, along with an additional 3.7% through the covariance with occupational categories. Occupations are strong drivers of the ability to WFH. One-digit groups account for 7.2% of the estimated variance, and this share increases to 14.2% at the three-digit level. The contribution of country fixed effects to the WFH variance is negligible (0.6-0.8%), indicating that cross-country differences in WFH in the STEP sample are largely explained by differential employment structures in these countries. Our estimates, combined with information on employment composition, can thus be used to compute WFH ability for other countries in the range of income per capita covered by the STEP countries ($3,000-$14,000).

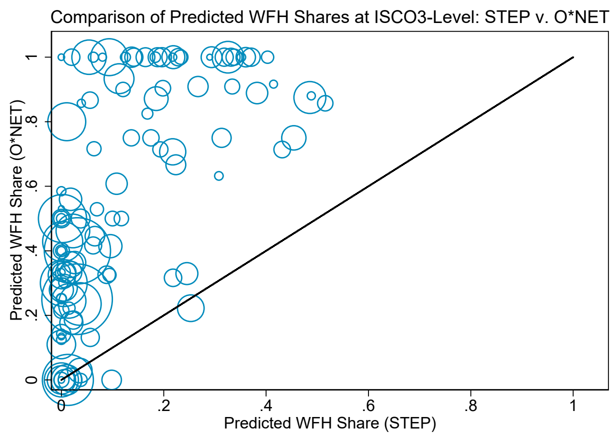
2.5 Comparison to Alternative Definitions

Recent work has documented important cross-country differences in task content even in the same occupation (Lo Bello et al., 2019; Lewandowski et al., 2019; Saltiel, 2019): for instance, the tasks performed by a cashier in Spain can differ significantly from those done by her counterpart in Bolivia. As such, extrapolating WFH measures using task-content information from developed countries — such as the O*NET — will not accurately capture cross-country differences in tasks. This is also the case for the ability to work from home.

We illustrate this point by comparing the estimated share of jobs which can be done from home in an occupation according to our measure to an analogous measure based on O*NET data. To do so, we take advantage of task questions in O*NET that are analogous to the the five task exclusions discussed in Section 2.2 to develop a directly comparable WFH measure.[12]

In Figure 1, we compare estimated WFH shares by occupation from STEP and from O*NET. The STEP-based measure indicates lower estimated likelihood of WFH in 93% of three-digit occupations.[13] This underlines the importance of using measures of WFH ability, measured in an appropriate context, for assessing the feasibility of WFH in developing countries.

Figure 1: Comparison of Estimated WFH Across STEP and O*NET



Source: Skills Toward Employability and Productivity (STEP) Survey and O*NET.
Note: Figure 1 presents the share of jobs which can be done from home at the three-digit occupation level following the measure introduced in Section 2.2. We compare the estimated WFH share to an O*NET-based equivalent measure to our WFH measure, as described in Section 2.5. We restrict the analysis to three-digit occupations with at least ten respondents in STEP. Results are weighted using STEP sample weights to represent the working-age population of 15-64 year olds.

3 Who is Working from Home?

In this section, we analyze the share of workers who actually worked from home during the second quarter of 2020 in Brazil and Costa Rica.[14] While the extent of social distancing policies varied in these two countries, the stringency index measure presented in Hale et al. (2020) places both countries far above the worldwide median. In fact, in Figure A1, we show that workplace mobility in both countries fell significantly in the second quarter of 2020, closely resembling the mobility drop experienced in the United States.

[12]We present a direct crosswalk of task measures in the O*NET and STEP in Table A3. Note that differences in within-occupation WFH shares between STEP and O*NET are not driven by differential survey designs, as the task questions used to measure WFH in both surveys are answered by incumbent workers (Handel, 2016).

[13]In Figure A4, we provide a comparison to Dingel and Neiman (2020)'s O*NET-based measure. Their measure uses a larger number of exclusions relative to ours. This tends to reduce WFH measures. Still, the STEP-based measure predicts a lower WFH likelihood in 78% of three-digit occupations, further highlighting differences in task content across contexts. In Table A4, we list WFH shares for these two measures by two-digit occupations.

[14]To the best of our knowledge, these are the only household surveys conducted during the pandemic in developing countries which include information on whether individuals are working from home.

3.1 Data Sources

Brazil. We use data from a nationally-representative survey of Brazilian households (PNAD COVID-19) carried out in May and June, 2020, which is an adaptation of Brazil's monthly household survey. PNAD COVID-19 interviewed Brazilian households remotely via telephone, covering questions related to health issues along with information on household members' employment outcomes.[15] As such, we observe detailed information on workers' labor market outcomes during the pandemic, including whether they worked in the previous week, their wage/self-employment status and one-digit occupations. Additionally, respondents report their age, educational attainment and gender. Critical to our analysis, PNAD COVID-19 includes a measure of whether respondents started working from home during the pandemic.

Costa Rica. We use information from Costa Rica's quarterly labor force survey (ECE), which was carried out telephonically in the second quarter of 2020. This survey included standard questions related to workers' labor market status, along with additional questions aimed at capturing outcomes during the pandemic. We observe whether respondents were employed in the previous week, their three-digit occupation and self-employment status, along with the same observed characteristics available in Brazil. Importantly, ECE includes a detailed question capturing workers' place of employment, which allows us to observe whether individuals 'teleworked' in the reference week. In light of the low prevalence of remote work in Latin America prior to Covid-19 (see Figure A5), the WFH measures available in Brazil and Costa Rica allow us to present initial evidence on the drivers of working from home in developing countries during the pandemic.

Sample Construction. For comparability with the STEP surveys, we restrict the sample to workers residing in urban areas across both countries. Moreover, we focus on prime-age workers (18-59 years old) who had worked in the week prior to the interview, and for whom we observe occupational information. Our sample covers 163,861 workers in Brazil and 3,221 in Costa Rica.

3.2 WFH Across Occupations and Characteristics

In Table 3, we present evidence on the share of employment being done remotely during the pandemic along with the types of individuals who are working from home. In the first panel, we show results for Brazil, where 13.3% of urban workers started working from home during May and June, 2020. The estimated share of WFH is far below the corresponding share for European countries (Dingel and Neiman, 2020; Adams-Prassl et al., 2020b; Eurofound, 2020), which ranged from 20% in Romania to upwards of 50% in Luxembourg. Nonetheless, there is substantial heterogeneity in the share of remote work across occupations, ranging from 23% for managers and 41% for professionals, while remaining at 1% for craft workers and machine operators. Differences in WFH associated with workers' observed characteristics fit in line with our predicted patterns, as the prevalence of WFH

[15] The main sample covered 349,306 individuals, drawn from Brazil's continuous monthly household survey.

is far higher among high school completers, wage employees, and women. These differences remain significant within most broad occupational groups, albeit with varying statistical significance. For instance, the estimated share of managers with a high school degree who started working from home in the pandemic exceeds the corresponding share for HS dropouts by 20 percentage points.

In the second panel of Table 3, we present evidence for Costa Rica, where 10.8% of urban workers worked remotely in the second quarter of 2020. As in Brazil, we find significant differences in the prevalence of WFH across occupations — about half of professionals worked from home, compared to almost no workers in lower-paying occupations. Furthermore, we find similar patterns across workers' observed characteristics, which indicate a higher prevalence of WFH for wage employees, high school graduates and women.

To the best of our knowledge, ours is the first paper to document the factors driving actual WFH in developing countries during the pandemic. Our results fit in with recent evidence across developed countries documenting a higher likelihood of remote work for more educated workers (Adams-Prassl et al., 2020b; Bick et al., 2020; Farré et al., 2020; Andrew et al., 2020; Alipour et al., 2020; Belot et al., 2020). Meanwhile, while women have borne a disproportionate share of employment losses in many countries, various papers have found that among those who work, actual WFH is more prevalent for women than for men. (Bick et al. (2020) present evidence on the U.S., Farré et al. (2020) on Spain, Andrew et al. (2020) on the UK.)[16]

The results presented so far for Brazil and Costa Rica match our STEP-based WFH measure, as workers' characteristics relate to the likelihood of having worked from home within broad occupational groups in a similar way as they do for the ability to WFH analyzed in the previous section. To assess the relative contribution of workers' characteristics and occupations to the prevalence of actual WFH, we estimate equation (1) in these two countries and present the results in Table A6. This shows that the estimated patterns documented above are robust to controlling for occupation. Importantly, more educated workers and wage employees are more likely to have worked from home even within narrowly-defined three-digit occupations in Costa Rica. This again illustrates that the work from home propensity varies not just across occupations, but that there also is significant heterogeneity within occupations.

3.3 Comparing Predicted and Actual WFH

Next, we compare the realized WFH measures from Brazil and Costa Rica to our STEP-based measures of potential WFH. Our STEP-based measure predicts significant heterogeneity in the prevalence of WFH across occupations. We first validate our measure by comparing the predicted prevalence of WFH across occupations relative to the share of telework in these jobs in Costa Rica (Figure A6).[17] Across both two- and three-digit occupations, our measure is a strong predictor of

[16] Adams-Prassl et al. (2020b) find that women report being able to do a smaller share of their job tasks from home. This measure differs from the binary measure of actual WFH considered in our paper and in Bick et al. (2020); Farré et al. (2020); Andrew et al. (2020).

[17] This exercise cannot be done for Brazil, as we do not observe detailed occupational codes there.

Table 3: Prevalence of Working from Home by Occupations and Characteristics

Panel A. Evidence from Brazil

		Educational Attainment		Self-Employment		Gender	
	Full Sample	HS Graduate	HS Dropout	Wage Employee	Self-Employed	Female	Male
One-Digit Occupation	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Managers	0.236	0.256	0.040***	0.264	0.225**	0.265	0.218***
Professionals	0.410	0.410	0.396	0.432	0.324***	0.412	0.406
Technicians and Associate Professionals	0.220	0.220	0.000	0.232	0.149***	0.295	0.184***
Clerical Support Workers	0.172	0.180	0.069***	0.172	.	0.171	0.174
Services and Sales Workers	0.038	0.050	0.010***	0.042	0.028***	0.049	0.027***
Skilled Agricultural, Forestry and Fishery Workers	0.007	0.018	0.001***	0.005	0.007	0.007	0.007
Craft and Related Trades Workers	0.011	0.019	0.005***	0.007	0.014***	0.027	0.008***
Plant and Machine Operators, and Assemblers	0.008	0.011	0.004***	0.008	0.008	0.012	0.008
Elementary Occupations	0.042	0.073	0.010***	0.023	0.104***	0.031	0.065***
Sample Average	0.133	0.182	0.011***	0.157	0.073***	0.178	0.098***
Observations	163861	116911	46950	114455	41958	70887	92974

Panel B. Evidence from Costa Rica

		Educational Attainment		Self-Employment		Gender	
	Full Sample	HS Graduate	HS Dropout	Wage Employee	Self-Employed	Female	Male
One-Digit Occupation	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Managers	0.208	0.208	.	0.217	.	0.385	0.000
Professionals	0.520	0.520	.	0.569	0.063***	0.526	0.510
Technicians and Associate Professionals	0.192	0.207	0.111*	0.213	0.042***	0.252	0.158*
Clerical Support Workers	0.243	0.272	0.073***	0.246	.	0.252	0.233
Services and Sales Workers	0.004	0.008	0.000	0.004	0.006	0.005	0.003
Skilled Agricultural, Forestry and Fishery Workers	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Craft and Related Trades Workers	0.002	0.007	0.000	0.005	0.000	0.011	0.000
Plant and Machine Operators, and Assemblers	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Elementary Occupations	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sample Average	0.108	0.203	0.005***	0.137	0.007***	0.162	0.071***
Observations	3221	1682	1539	2512	593	1314	1907

Source: PNAD-COVID19 (Brazil) and *Encuesta Continua de Empleo* (ECE, Costa Rica). Note: Table 3 documents the share of workers who are working from home in Brazil and Costa Rica by one-digit occupation, educational attainment, self-employment and gender. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the prevalence of WFH, as the majority of occupational averages lie close to the 45 degree line. For instance, our measure predicts that 16.4% of sales agents and brokers could work from home, and 15.5% of them in fact teleworked in Costa Rica during the second quarter of 2020.

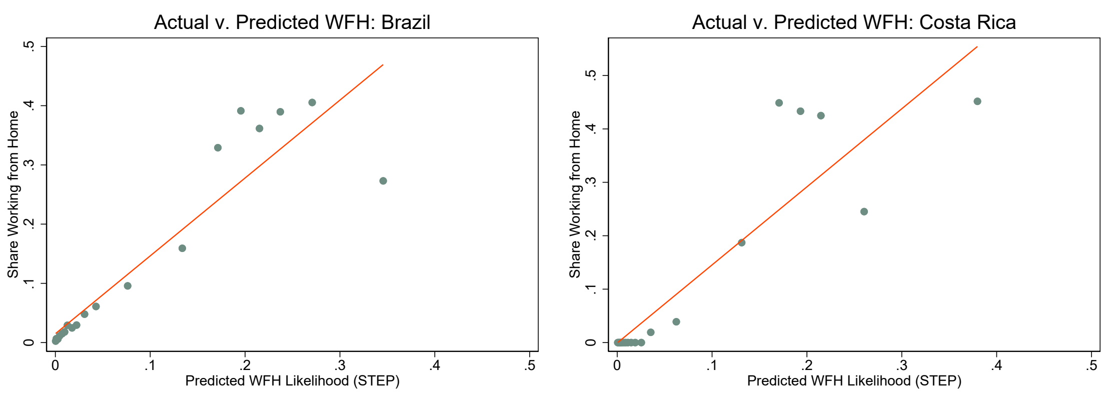
At the same time, our preferred measure additionally considers workers' characteristics in predicting their ability to work from home. We thus present evidence from an empirical exercise which leverages differential WFH ability across occupations and observed characteristics. In particular, in the STEP sample, we estimate a probit of the predicted likelihood of WFH including workers' characteristics and their one-digit occupation. We then use the estimated coefficients from the regression to impute a STEP-predicted WFH likelihood for each worker in the Brazil and Costa Rican samples. We subsequently compare the STEP-predicted work from home probability against workers' actual WFH outcomes during the pandemic in these two countries in a binned scatter plot. In each country, we divide the predicted probabilities in twenty equal-sized groups and compare it to the share of workers in the bin who are actually working from home.

We present the results in Figure 2. In Brazil, the estimated share of individuals who worked from home in the second quarter of 2020 rises along with their predicted WFH probabilities from the STEP sample. In Costa Rica, meanwhile, a substantial share of workers did not telework during the pandemic. For these workers, we had predicted WFH probabilities below 3%. Similar to Brazil, we predict a higher likelihood of being able to work from home for workers who were more likely to have actually teleworked in Costa Rica.

We extend this analysis by estimating a regression of predicted WFH probabilities against a binary variable capturing whether workers actually worked from home during the pandemic. In the first and fourth columns of Table A7, we present evidence from bivariate regressions in Brazil and Costa Rica, finding that a one standard deviation increase in our measure is associated with an increased likelihood of working from home by 14.1 and 15.8 percentage points, respectively. In fact, this simple regression denotes the strong predictive power of our measure, as the estimated R^2 equals 0.173 in Brazil and reaches 0.249 in Costa Rica.[18] The remaining columns indicate these patterns are robust to the separately controlling for worker characteristics and occupations.

These two validation exercises highlight the usefulness of STEP data for predicting the WFH ability of different groups (Figures 2 and A6) or even individuals (Table A7). Our predicted WFH probabilities are largely similar in levels to those actually observed in both countries, and are strongly predictive of actual outcomes. This gives us confidence in the transferability of our estimates from STEP to other countries in the same broad income range.

Figure 2: Predicted and Observed WFH in Brazil and Costa Rica



(a) Brazil

(b) Costa Rica

Source: Skills Towards Employability and Productivity (STEP) Survey, PNAD-COVID19 (Brazil) and *Encuesta Continua de Empleo* (ECE, Costa Rica). Note: Figure 2 documents the relationship between the prevalence of remote work in Brazil and Costa Rica against the predicted WFH probability from the STEP sample. In STEP, we estimate a probit of the predicted likelihood of WFH including workers' characteristics and their one-digit occupation. We compare the STEP-predicted WFH probability against actual outcomes in two countries by dividing the predicted probabilities in twenty equal-sized groups. We then compare it to the estimated to the share of workers in each bin who are working from home.

[18] We alternatively consider the goodness of fit using a prediction which solely relies on WFH-ability variation at the occupational level. The estimated fit is worse relative to our preferred measure, as the R^2 for Brazil falls to 0.137 and to 0.218 in Costa Rica.

4 Conclusion

Social distancing and stay-at-home policies play a critical role in stopping the spread of COVID-19. In this context, the negative employment and health impacts arising from COVID-19 may be muted if workers are able to perform their jobs at home. Yet measuring the ability to WFH in developing countries is not a straight-forward endeavor, given limited information on task content in these countries. In this paper, we have first introduced a work from home measure for these countries, which follows from a worker-level survey on their task content. Our analysis indicates that fewer than 10% of urban jobs in developing countries could be done remotely, and our measure allows us to further document important differences in the ability to WFH across workers' characteristics and occupations. Various vulnerable groups are less likely to work remotely, including workers in low-wage occupations, high school dropouts and self-employed individuals. In the second part of the paper, we have taken advantage of recent data capturing employment outcomes during the pandemic in two developing countries, Brazil and Costa Rica. In these two countries, the prevalence of actual WFH in the second quarter of 2020 was relatively low, in line with our preferred measure. Moreover, there is substantial heterogeneity in the types of workers who have actually been able to work from home. Since a far smaller share of vulnerable workers have been able to carry out their jobs from home, they are more likely to have been exposed to Covid-19. Our analysis thus provides valuable information on the groups of the population that are hit hardest by policies that aim at taming the spread of the pandemic. As such, this paper includes valuable information for policy makers to design policies that are targeted to workers that are most adversely hit by the economic consequences of the pandemic. Our findings should also prove useful to the quantitative analysis of the effects of social distancing, including the study of optimal policies.

References

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh (2020a). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics 189*.

Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh (2020b). Work tasks that can be done from home: Evidence on the variation within and across occupations and industries. *mimeo*.

Alipour, J.-V., O. Falck, and S. Schaller (2020). Germany's capacities to work from home.

Andrew, A., S. Cattan, M. Costa Dias, C. Farquharson, L. Kraftman, S. Krutikova, A. Phimister, and A. Sevilla (2020). The gendered division of paid and domestic work under lockdown.

Autor, D. H. and M. J. Handel (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics 31*(S1), S59–S96.

Belot, M., S. Choi, J. C. Jamison, N. W. Papageorge, E. Tripodi, and E. Van den Broek-Altenburg (2020). Unequal consequences of Covid 19 across age and income: Representative evidence from six countries.

Bick, A., A. Blandin, and K. Mertens (2020). Work from home after the Covid-19 outbreak.

Boeri, T., A. Caiumi, and M. Paccagnella (2020). Mitigating the work-security trade-off while rebooting the economy. *Covid Economics 2*.

del Rio-Chanona, R. M., P. Mealy, A. Pichler, F. Lafond, and D. Farmer (2020). Supply and demand shocks in the covid-19 pandemic: An industry and occupation perspective. *Covid Economics 6*.

Dicarlo, E., S. L. Bello, S. Monroy-Taborda, A. M. Oviedo, M. L. Sanchez-Puerta, and I. Santos (2016). The Skill Content of Occupations Across Low and Middle Income Countries: Evidence from Harmonized Data. *IZA DP No. 10224*.

Dingel, J. and B. Neiman (2020). How many jobs can be done at home? *Journal of Public Economics 189*.

Eurofound (2020). Living, working and Covid-19: first findings, April 2020.

Fadinger, H., J. Schymik, et al. (2020). The effects of working from home on Covid-19 infections and production a macroeconomic analysis for germany. *Covid Economics 9*.

Farré, L., Y. Fawaz, L. González, and J. Graves (2020). How the covid-19 lockdown affected gender inequality in paid and unpaid work in Spain.

Garrote Sanchez, D., N. Gomez Parra, C. Ozden, B. Rijkers, M. Viollaz, and H. Winkler (2020). Who on earth can work from home?

Gottlieb, C., J. Grobovšek, and M. Poschke (2020). Working from home across countries. *Covid Economics 7*.

Hale, T., S. Webster, A. Petherick, T. Phillips, and B. Kira (2020). Oxford Covid-19 government response tracker. *Blavatnik School of Government 25*.

Handel, M. J. (2016). The o* net content model: strengths and limitations. *Journal for Labour Market Research 49*(2), 157–176.

Hatayama, M., M. Viollaz, and H. Winkler (2020). Jobs' amenability to working from home: Evidence from skills surveys for 53 countries. *World Bank Policy Research Working Paper* (9241).

Hensvik, L., T. Le Barbanchon, and R. Rathelot (2020). Which jobs are done from home? Evidence from the American Time Use Survey.

Lewandowski, P., A. Park, W. Hardy, and Y. Du (2019). Technology, skills, and globalization: Explaining international differences in routine and nonroutine work using survey data. *IZA DP No. 12339*.

Lo Bello, S., M. L. Sanchez Puerta, and H. Winkler (2019). *From Ghana to America: The Skill Content of Jobs and Economic Development*.

Mongey, S. and A. Weinberg (2020). Characteristics of workers in low work-from-home and high personal-proximity occupations.

Saltiel, F. (2019). Comparative Evidence on the Returns of Tasks in Developing Countries. *mimeo*.

Saltiel, F. (2020). Who can work from home in developing countries. *Covid Economics 7*, 104–118.

Stinebrickner, R., T. Stinebrickner, and P. Sullivan (2019). Job Tasks, Time Allocation, and Wages. *Journal of Labor Economics 37*(2), 399–433.

Appendices

A Appendix Tables and Figures

Table A1: Share of Work-from-Home by One-Digit Occupation and Country

	All (1)	Armenia (2)	Bolivia (3)	China (4)	Colombia (5)	Georgia (6)	Ghana (7)	Kenya (8)	Laos (9)	Macedonia (10)	Vietnam (11)
Sample Average	0.093	0.104	0.060	0.143	0.058	0.154	0.032	0.074	0.033	0.123	0.141
Manager	0.238	0.311	0.102	0.156	0.161	0.312	0.186	0.225	0.187	0.263	0.419
Professional	0.196	0.116	0.117	0.223	0.234	0.184	0.136	0.24	0.115	0.232	0.391
Technician	0.2	0.14	0.17	0.243	0.103	0.244	0.148	0.293	0.178	0.174	0.345
Clerical	0.282	0.304	0.199	0.332	0.21	0.37	0.119	0.309	0.237	0.218	0.315
Services/Sales	0.03	0.027	0.035	0.058	0.031	0.076	0.005	0.012	0.003	0.044	0.044
Agricultural	0.001	0	0.05	0	0	0	0	0	0	0	0
Craft/Trades	0.012	0.01	0.007	0.027	0.009	0.018	0.011	0.014	0	0.014	0.016
Machine Operators	0.007	0.024	0.009	0.023	0	0	0	0	0	0.004	0.005
Elementary Occupations	0.013	0.006	0.01	0.064	0.005	0.017	0.005	0.002	0	0.021	0.011

Source: Skills Toward Employability and Productivity (STEP) Survey. Note: Table A1 presents evidence on the share of workers who can work from home by one-digit occupation and country. Results are weighted using sample weights to represent the working-age population of 15-64 year olds.

Table A2: Variance decomposition of working from home: share explained by different factors

% Explained	(1)	(2)
Variance	1.000	1.000
$Var(X_i)$	0.022	0.018
$Var(\gamma_O)$	0.072	0.142
$Var(\lambda_c)$	0.008	0.006
$Cov(X_i, \gamma_O)$	0.038	0.037
$Cov(X_i, \lambda_c)$	-0.001	0
$Cov(\gamma_O, \lambda_c)$	-0.002	0
$Var(\varepsilon_{ioc})$	0.862	0.797
R^2	0.137	0.202
Occ FE	One-Digit	Three-Digit
Observations	17,592	

Source: Skills Toward Employability and Productivity (STEP) Survey. Note: Table A2 presents a variance decomposition following equation (1). The 'Variance' row denotes the share of the variance in the WFH measure to be explained and all the rows below denote the share of the variance accounted by each variable. The first and second columns include one- and three- digit occupation fixed effects, respectively. Results are weighted using sample weights to represent the working-age population of 15-64 year olds in the sample.

Table A3: Work from home measurement: STEP v. O*NET

Questionnaire	ONET	STEP
Section	*Work context*	*Skills at work*
1	Performing General Physical Activities is very important (4.0+ of 5)	Do you regularly have to lift or pull anything weighing at least 25 kilos? Binary response.
2	Repairing and Maintaining Electronic Equipment is very important (4.0+ of 5)	As part of this work, do you (did you) repair/maintain electronic equipment? Binary response.
3	Operating Vehicles, Mechanized Devices, or Equipment is very important (4.0+ of 5)	As part of this work, do you (did you) operate or work with any heavy machines or industrial equipment ?
4	Performing for or Working Directly with the Public is very important (4.0+ of 5)	Time involved with customers. Ranked on a scale from 1-10 only for workers who answered positively to "Do you contact non-coworkers?" Deemed important if responded with a 9 or 10.
Section	*Generalized work activities*	
5	"Average respondent says they use email less than once per month"	Does your work require the use of the following [e-mail]? Binary response.

Note: Table A3 presents a correspondence between the task measures used to construct the WFH measure in STEP and O*NET, as discussed in Section 2.5. The questions in the STEP column are taken from this questionnaire. O*NET task measures follow from the 'Work Context' and 'Work Activities' modules.

Table A4: Work from Home employment by definition and two-digit ISCO occupations.

Occupation name (ISCO 2)	WFH employment, STEP	WFH employment, Dingel and Niemann
Chief Executives, Senior Officials and Legislators	0.28	0.66
Administrative and Commercial Managers	0.25	0.89
Production and Specialized Services Managers	0.25	0.67
Hospitality, Retail and Other Services Managers	0.20	0.13
Science and Engineering Professionals	0.30	0.67
Health Professionals	0.09	0.12
Teaching Professionals	0.09	0.96
Business and Administration Professionals	0.42	0.94
Information and Communications Technology Professionals	0.29	1.00
Legal, Social and Cultural Professionals	0.24	0.68
Science and Engineering Associate Professionals	0.16	0.16
Health Associate Professionals	0.06	0.04
Business and Administration Associate Professionals	0.29	0.70
Legal, Social, Cultural and Related Associate Professionals	0.16	0.56
Information and Communications Technicians	0.26	0.84
General and Keyboard Clerks	0.34	1.00
Customer Services Clerks	0.25	0.31
Numerical and Material Recording Clerks	0.27	0.55
Other Clerical Support Workers	0.22	0.65
Personal Services Workers	0.03	0.17
Sales Workers	0.03	0.17
Personal Care Workers	0.04	0.18
Protective Services Workers	0.04	0.10
Market-oriented Skilled Agricultural Workers	0.00	0.04
Market-oriented Skilled Forestry, Fishery and Hunting Workers	0.00	0.03
Subsistence Farmers, Fishers, Hunters and Gatherers	0.00	0.00
Building and Related Trades Workers (excluding electricians)	0.02	0.01
Metal, Machinery and Related Trades Workers	0.01	0.00
Handicraft and Printing Workers	0.04	0.25
Electrical and Electronics Trades Workers	0.01	0.00
Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	0.00	0.11
Stationary Plant and Machine Operators	0.01	0.00
Assemblers	0.00	0.00
Drivers and Mobile Plant Operators	0.01	0.01
Cleaners and Helpers	0.00	0.00
Agricultural, Forestry and Fishery Labourers	0.01	0.00
Labourers in Mining, Construction, Manufacturing and Transport	0.01	0.03
Food Preparation Assistants	0.00	0.00
Street and Related Sales and Services Workers	0.07	0.00
Refuse Workers and Other Elementary Workers	0.02	0.19

Note: Table A4 compares the estimated WFH shares at the two-digit occupation level using different measures. Column 1 reports the share of WFH employment at the ISCO-2 occupationu-level sing the measure outlined in section 2.2 based on STEP data. Column 2 reports the share of WFH employment as measured by Dingel and Neiman (2020) based on O*NET data.

Table A5: Predicted WFH by Occupations and Characteristics in STEP

Gender		Males				Females			
Education		HS Graduate		HS Dropout		HS Graduate		HS Dropout	
Self-Employment	Full Sample	Wage	Self	Wage	Self	Wage	Self	Wage	Self
One-Digit Occupation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Managers	0.238	0.308	0.166	0.173	0.115	0.311	0.211	0.061	0.042
Professionals	0.196	0.216	0.179	0.020	0.164	0.201	0.125	0.108	0.123
Technicians and Associate Professionals	0.200	0.231	0.091	0.113	0.036	0.231	0.228	0.074	0.000
Clerical Support Workers	0.282	0.218	0.337	0.134	0.105	0.372	0.192	0.138	0.000
Services and Sales Workers	0.030	0.054	0.047	0.017	0.015	0.076	0.031	0.012	0.004
Skilled Agricultural, Forestry and Fishery Workers	0.001	0.007	0.006	0.000	0.000	0.000	0.000	0.000	0.000
Craft and Related Trades Workers	0.012	0.014	0.039	0.004	0.006	0.034	0.014	0.000	0.004
Plant and Machine Operators, and Assemblers	0.007	0.017	0.008	0.000	0.000	0.014	0.000	0.000	0.000
Elementary Occupations	0.013	0.029	0.000	0.001	0.000	0.049	0.082	0.001	0.006
Sample Average	0.093	0.143	0.081	0.019	0.014	0.191	0.067	0.022	0.005
Observations	17592	3599	1299	1923	1422	3915	1277	1658	2499

Source: Skills Toward Employability and Productivity (STEP) Survey. Note: Table A5 documents the share of workers who can work from home by 72 categories encompassing one-digit occupation, educational attainment, self-employment and gender. Results are weighted using sample weights to represent the working-age population of 15-64 year olds in each STEP country.

Table A6: Determinants of WFH in Brazil and Costa Rica

	Brazil		Costa Rica		
	(1)	(2)	(3)	(4)	(5)
Educational Attainment	0.028***	0.013***	0.030***	0.005***	0.003**
	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)
Age	0.003***	0.001***	0.001***	-0.000	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	-0.033***	-0.004**	-0.031***	-0.018	-0.011
	(0.002)	(0.002)	(0.011)	(0.011)	(0.013)
Wage Employment	0.037***	0.013***	0.076***	0.045***	0.016**
	(0.002)	(0.002)	(0.007)	(0.008)	(0.008)
Observations	156413	133227	3104	3104	3104
R^2	0.141	0.228	0.202	0.342	0.534
Occupation FE	None	One-Digit	None	One-Digit	Three-Digit

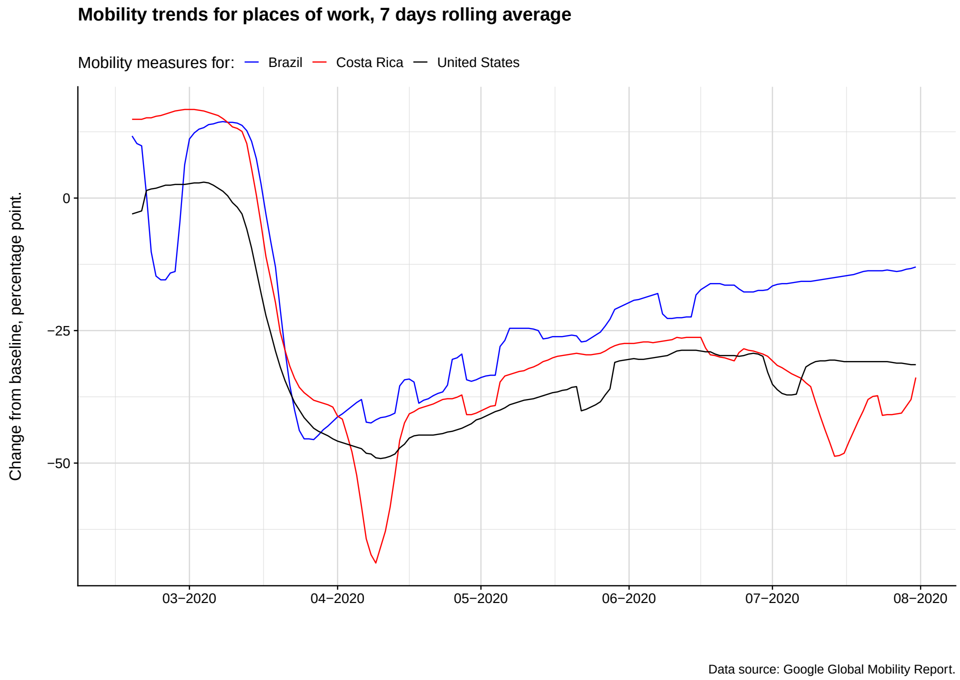
Source: PNAD-COVID19 (Brazil) and *Encuesta Continua de Empleo* (ECE, Costa Rica). Table A6 presents the estimated coefficients from equation (1) across different specifications using employment outcomes in Brazil and Costa Rica in the second quarter of 2020. The first and third columns do not include occupation fixed effects, whereas the second and fourth columns include one-digit occupation fixed effects, respectively. The last column incorporates three-digit occupation fixed effects in Costa Rica. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Predicted and Observed WFH in Brazil and Costa Rica: Regression Results

		Brazil			Costa Rica	
	(1)	(2)	(3)	(4)	(5)	(6)
WFH-STEP (Standardized)	0.141***	0.105***	0.171***	0.158***	0.124***	0.082***
	(0.001)	(0.001)	(0.003)	(0.008)	(0.010)	(0.021)
Educational Attainment		0.014***	0.003***		0.009***	-0.002**
		(0.000)	(0.000)		(0.002)	(0.001)
Age		0.003***	0.002***		0.001***	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Male		-0.005***	0.008***		-0.012	-0.009
		(0.002)	(0.002)		(0.010)	(0.011)
Wage Employment		-0.005***	-0.011***		0.037***	0.040***
		(0.002)	(0.002)		(0.006)	(0.008)
Observations	133227	133227	133227	3104	3104	3104
R^2	0.173	0.196	0.250	0.249	0.259	0.350
Occupation FE	None	None	One-Digit	None	None	One-Digit

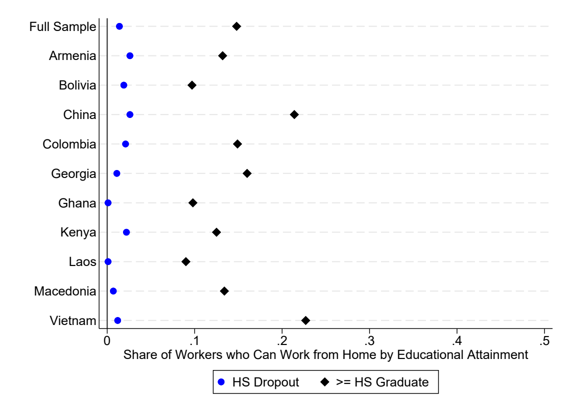
Source: Skills Towards Employability and Productivity (STEP) Survey, PNAD-COVID19 (Brazil) and *Encuesta Continua de Empleo* (ECE, Costa Rica). Note: Table A7 documents the relationship between the prevalence of remote work in Brazil and Costa Rica against the predicted WFH probability from the STEP sample. The estimated WFH probability follows from a probit model in the STEP sample which includes workers' characteristics and one-digit occupations. We standardize the WFH-STEP measure to be mean zero and variance one, for ease of interpretation. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Mobility Trends for Workplaces in Brazil, Costa Rica and the US

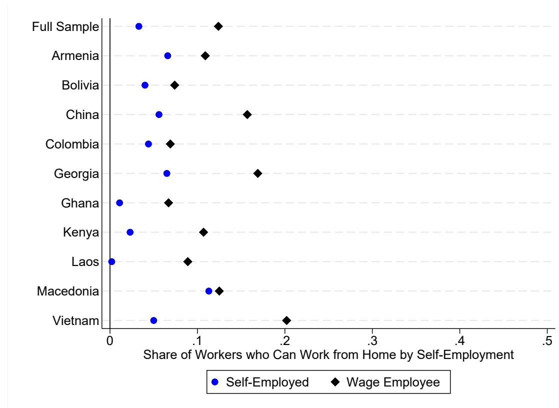


Note: Figure A1 documents the extent of changes in individuals' work-based mobility in Brazil, Costa Rica and the United States from March, 2020 through August, 2020.

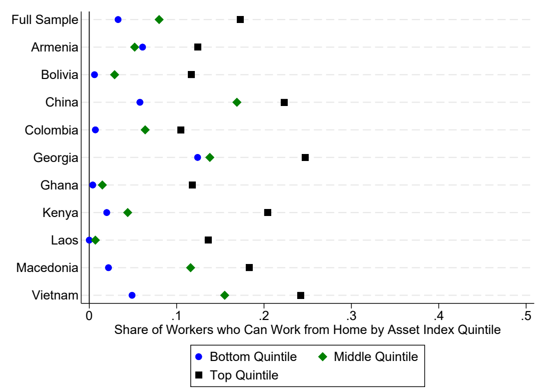
Figure A2: Characteristics of Work-From-Home Workers, by Country



(a) By HS Dropout Status



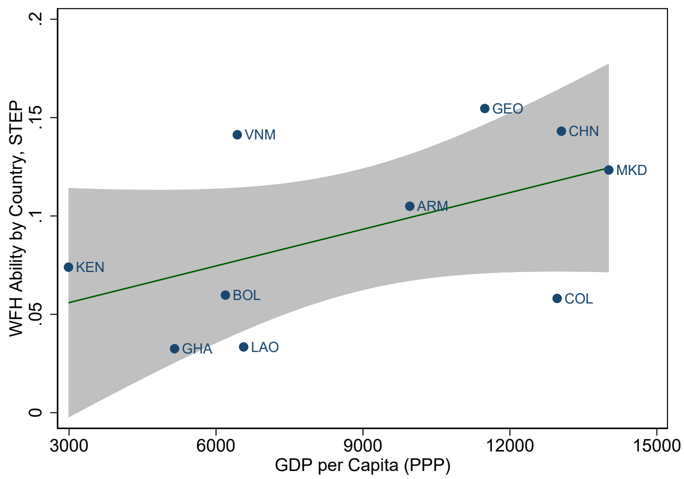
(b) By Self-Employment



(c) By Asset-Index Quintile

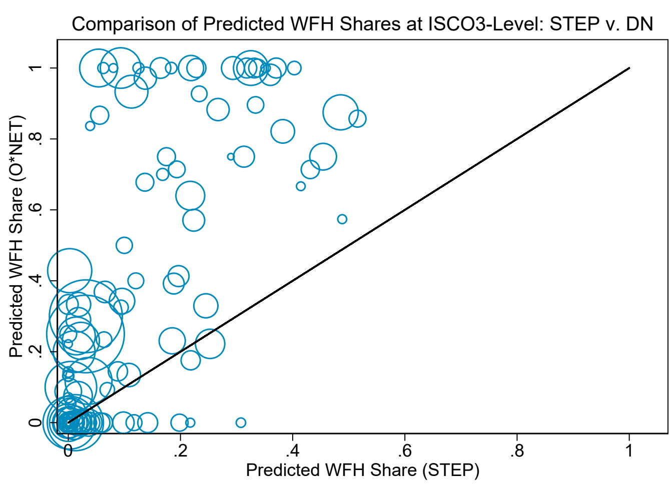
Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure A2 presents the share of jobs which can be done from home in the full sample and across STEP countries by workers' high school dropout status (Panel A), self-employment status (Panel B), and asset index quintile (Panel C). Results are weighted using sample weights to represent the working-age population of 15-64 year olds.

Figure A3: Work from home ability across countries



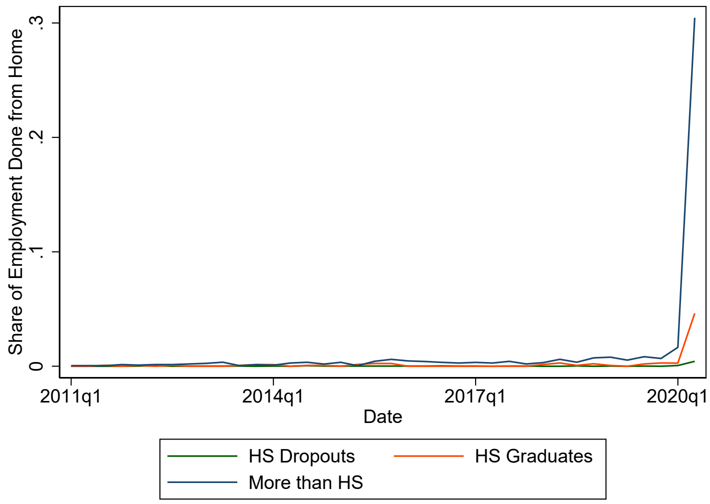
Source: Skills Toward Employability and Productivity (STEP). Note: Figure A3 presents the estimated share of jobs which can be done from home across countries in the STEP sample.

Figure A4: Comparison of Estimated WFH to Dingel and Neiman (2020)



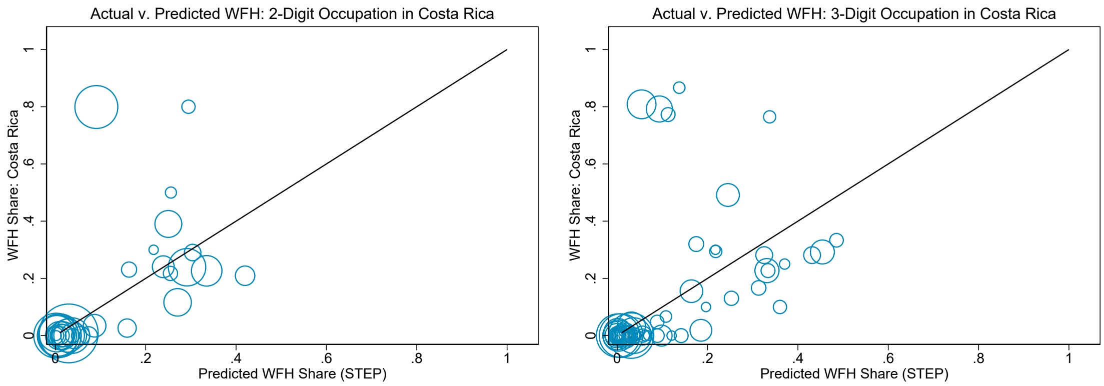
Source: Skills Toward Employability and Productivity (STEP). Note: Figure A4 presents the share of jobs which can be done from home at the three-digit occupation level following the measure introduced in Section 2.2. We compare the estimated WFH share to Dingel and Neiman (2020). We restrict the analysis to three-digit occupations with at least ten respondents in STEP. Results are weighted using STEP sample weights to represent the working-age population of 15-64 year olds.

Figure A5: Prevalence of WFH in Costa Rica by Education, 2011-2020



Source: *Encuesta Continua de Empleo* (ECE in Costa Rica). Note: Figure A5 documents the extent of telework in Costa Rica between 2011 and 2020 by workers' educational attainment, covering high school dropouts, high school graduates and those who went beyond high school.

Figure A6: Comparison of Predicted and Observed WFH in Costa Rica, by Occupations



(a) Two-Digit Occupation **(b)** Three-Digit Occupation

Source: Skills Toward Employability and Productivity (STEP) Survey and *Encuesta Continua de Empleo* (ECE in Costa Rica).
Note: Figure A6 presents the share of jobs which can be done from home at the two and three-digit occupation level following the measure introduced in Section 2.2. We compare the estimated WFH share to the share of jobs being done from home across two- and three-digit occupations in Costa Rica in the second quarter of 2020. We restrict the analysis to occupations with at least ten respondents in both STEP and ECE. Results are weighted using STEP sample weights to represent the working-age population of 15-64 year olds in STEP.