Who Can Work From Home in Developing Countries?

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Abstract

In this paper, I examine the feasibility of working from home in developing countries. I take advantage of worker-level data from the STEP survey, which collects comparable information on employment outcomes across ten countries. I use information on workers' tasks to define the feasibility of working from home following Dingel and Neiman (2020). Only 13% of workers in STEP countries could work from home, yet this share ranges from 5.5% in Ghana to 23% in Yunnan (China). The feasibility of working from home is positively correlated with high-paying occupations. Educational attainment, formal employment status and household wealth are positively associated with the possibility of working from home, reflecting the vulnerability of various groups of workers. These relationships remain significant *within* narrowly defined occupations, yet exhibit heterogeneity across countries. I remark the importance of rapidly identifying vulnerable workers to design adequate policies to combat the negative employment impacts of COVID-19.

Keywords: COVID-19, Occupations, Tasks, Comparative Analysis.

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1 Introduction

Governments across the world have implemented social distancing and stay-at-home policies to stop the spread of COVID-19. A critical consideration for understanding the negative labor market impacts arising from the virus is whether workers can plausibly work from home. Two recent papers have contributed important evidence in this dimension in the United States by taking advantage of task-content information in occupational dictionaries such as the O*NET (Dingel and Neiman, 2020; Mongey and Weinberg, 2020). However, their analysis 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; Saltiel, 2019). In fact, the limited availability of occupational dictionaries in these countries exacerbates the challenge of correctly measuring the share and the types of jobs which can be done from home.

In this paper, I examine the share of jobs which can be done from home in developing countries, as well as the worker characteristics associated with such jobs. I take advantage of worker-level data on task content from the Skills Toward Employability and Productivity (STEP) survey, which follows workers in urban areas across ten low- and middle-income countries, including Armenia, Bolivia, Yunnan Province in China, Colombia, Georgia, Ghana, Kenya, Laos, Macedonia and Vietnam. STEP covers comparable information on employment outcomes across countries, including details on workers' occupations, formal employment status, and tasks performed at work. As a result, I can examine within-occupation heterogeneity in workers' ability to work from home (Autor and Handel, 2013). Furthermore, STEP includes detailed information on observable characteristics, including educational attainment, gender and an asset index, allowing me to consider which workers are less likely to be able to work from home.

As a first approximation to the feasibility of working from home, I consider workers who report using a computer at work. While 29.5% of workers in the sample use a computer at work, there are important cross-country differences, reaching 58% of workers in Macedonia, compared to just 14% of their counterparts in Laos. My preferred work-from-home definition follows Dingel and Neiman (2020). It rules out working from home if workers either (not) use a computer at work, lift heavy objects, repair electronic equipment, operate heavy machinery or report that customer interaction is very important. 12.9% of workers in the full STEP sample are deemed to be able to work from home, which is far below the corresponding share in the U.S. (which equals 34% according to Dingel and Neiman (2020)).[1] I remark important cross-country differences in this measure, as well, as the share of individuals who may work from home reaches 23% in Yunnan compared to just 5.5% of workers in Ghana. Lastly, across all countries, the likelihood of working from home is positively correlated with high-paying occupations, such as managers and professionals, yet a high share of workers in clerical jobs may be able to do so, too.

I further examine the characteristics of workers who may be able to work from home. Across all STEP countries, workers' educational attainment, household wealth, gender and age strongly

[1] The analysis is restricted to urban areas in these countries, which likely overstates the share of jobs which can be done from home in the ten STEP countries.

predict their ability to work from home. For instance, the sample average indicates that just 4% of high school dropouts can work from home, compared to 24% of their more educated peers. I further document an important wealth gradient, as only 2.8% of households in the within-country bottom wealth quintile can work from home, compared to 25% of their counterparts in the top quintile, thus highlighting the challenge faced by households with limited access to self-insurance. Informal and self-employed workers are more vulnerable to the consequences from COVID-19 across all countries in STEP, as well. These relationships remain significant in a regression of worker-level work-from-home measures against all observed characteristics. To examine whether these patterns remain within narrowly-defined (three digit) occupations, I include occupation fixed effects and find that while occupations are important determinants of the feasibility of working from home in developing countries, vulnerable workers are less likely to do so even within occupations. Since the estimated patterns vary across countries, I remark the importance of rapidly identifying vulnerable workers and designing country-specific policies to limit the negative labor market impacts arising from the spread of COVID-19.

This paper makes various contributions to the literature on the feasibility of working from home. First, it fits in with two recent papers, which measure the extent of low work-from-home occupations in the United States along with worker characteristics associated with these jobs (Dingel and Neiman, 2020; Mongey and Weinberg, 2020).[2] As such, this paper also fits in with recent work by Mas and Pallais (2017) regarding the prevalence of flexible work arrangements. By taking advantage of worker-level data on task content, this paper contributes to the existing literature highlighting within-occupation differences in the importance of tasks (Autor and Handel, 2013; Stinebrickner et al., 2018, 2019). I lastly contribute to recent work which presents comparable evidence on the importance of tasks across countries (Dicarlo et al., 2016; Lo Bello et al., 2019; Lewandowski et al., 2019).

The rest of the paper proceeds as follows. Section 2 describes data sources and presents summary statistics. Section 3 presents evidence on the share of jobs that can be done from home, along with the worker characteristics associated with the possibility of home-based work. In Section 4, I discuss the results and conclude.

2 Data Sources and Summary Statistics

I take advantage of data from the Skills Toward Employment and Productivity (STEP) household survey, conducted in urban areas in developing countries by the World Bank. I use information from the first and second survey rounds, which covered workers in ten developing countries, including Armenia, Bolivia, Yunnan Province in China, Colombia, Georgia, Ghana, Kenya, Laos, Macedonia and Vietnam.[3] STEP surveys are representative of the working age population in urban areas in

[2] Leibovici et al. (2020) also provide important evidence on the extent of contact-intensive tasks in the United States by occupation.

[3] STEP also conducted surveys in Sri Lanka and Ukraine. I exclude Sri Lanka from the analysis for comparability, as sample largely covered workers in rural areas. Meanwhile, the Ukraine sample does not include information on

these countries, yet collect demographic information on all individuals in the household along with detailed information on employment outcomes for a randomly selected 15-64 year old household member. Since STEP collects detailed information on dwelling characteristics and household assets to construct a wealth-based asset index in each country (Pierre et al., 2014), I consider their quintile ranking in the asset index distribution as a measure of their capacity to cope with the shock.

I observe the main respondent's age, gender and educational attainment, along with detailed information on their employment outcomes, including whether they are currently employed and/or have been in the past twelve months. Respondents report whether they last worked as employees, in self-employment or as unpaid workers in the family business and whether they are employed in a formal or informal job, as defined by the presence of pension benefits.[4] Lastly, STEP includes information on workers' occupations at the one-digit level, encompassing managers, plant workers, among others, and the three-digit level under the harmonized ISCO-08 classification. I restrict the analysis to workers who have been employed in the past twelve months and drop those in unpaid family work or in the armed forces, given the lack of information on their occupational outcomes.

To measure the feasibility of working from home, I take advantage of worker-level data on the tasks performed at work (Dingel and Neiman, 2020; Mongey and Weinberg, 2020). As remarked by Dicarlo et al. (2016), Lo Bello et al. (2019) and Saltiel (2019), an important advantage of the STEP survey is the availability of worker-level task content, which allows me to examine within-occupation heterogeneity in workers' capacity to work from home. Moreover, since all STEP surveys include the same task content questions, the analysis is directly comparable across countries. The first measure of the feasibility of working from home follows directly from a binary response to whether workers use a computer at work. My preferred definition follows Dingel and Neiman (2020) and rules out working from home if workers report performing *either* of the following tasks at work: not using a computer, lifting anything heavier than 50 pounds, repairing/maintaining electronic equipment, operating heavy machinery or industrial equipment, or reporting that contact with customers is very important. Dingel and Neiman (2020) define an occupation as one that cannot be done from home if one of eighteen conditions holds true. Moreover, they assume that jobs cannot be performed from home unless they use e-mail, whereas my definition for developing countries focuses on computer use. As such, my definition could be considered as an upper bound on the share of jobs which can be done from home in these countries, yet it is possible that certain home-based jobs may not require a computer; such as workers in call centers. Since this paper is a first approximation on the feasibility of working from home in developing countries, I remark the need for further work in refining this definition.

Summary Statistics. Table 1 presents summary statistics for the sample used in the paper, which includes upwards of 17,000 workers in the full sample. I use sample weights to make the

workers' three-digit occupations. Throughout the paper, the discussion of results in China is limited to the Yunnan Province.

[4] I observe formal employment status only for workers employed at the time of the survey.

samples representative of the working-age populations in each country.[5] On average, respondents in the STEP survey have completed 10.2 years of education, yet there are important cross-country differences which positively correlate with levels of economic development. In terms of employment outcomes, there is a high prevalence of self-employment and informality in the full sample — reaching 43% and 66% of all workers, respectively — and these measures are negatively correlated with countries' GDP per capita.[6] The task measures indicate that a small share of workers in the full sample either repair electronic equipment or operate heavy machinery, reaching 7% in the full sample However, almost 40% of workers lift heavy items at work and 27% report having frequent interactions with their customers. The prevalence of these tasks also varies across countries, as only 16.7% of Ghanaian workers frequently contact customers compared to 38% of their Colombian counterparts. Lastly, 29.5% of workers in the sample use a computer at work, yet are important differences across countries, which I further explore in the next section.

Table 1: Summary Statistics

	All	Armenia	Bolivia	China	Colombia	Georgia	Ghana	Kenya	Laos	Macedonia	Vietnam
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Observables											
Years of Education	10.2	13.787	11.158	12.634	10.052	15.237	8.343	9.161	8.379	13.561	11.092
Male	0.467	0.412	0.461	0.522	0.46	0.395	0.438	0.55	0.418	0.522	0.432
Age	36.111	40.283	34.137	39.506	35.135	39.761	36.414	32.324	38.31	41.413	39.479
Employment Outcomes											
Self-Employed	0.427	0.104	0.419	0.137	0.45	0.139	0.612	0.396	0.636	0.147	0.398
Informal	0.661	0.173	0.771	0.456	0.633	0.611	0.836	0.743	0.855	0.142	0.58
Tasks											
Repair Items	0.073	0.257	0.063	0.184	0.053	0.063	0.061	0.067	0.023	0.09	0.086
Operate Machinery	0.074	0.06	0.079	0.054	0.098	0.064	0.054	0.071	0.041	0.084	0.053
Lift Heavy	0.384	0.268	0.45	0.24	0.393	0.275	0.477	0.374	0.532	0.254	0.324
Contact Others	0.273	0.353	0.223	0.3	0.38	0.361	0.167	0.319	0.109	0.407	0.087
Computer Use	0.295	0.431	0.316	0.545	0.324	0.44	0.112	0.225	0.14	0.577	0.34
Observations	17,616	1,092	1,848	1,298	1,930	1,076	2,223	2,529	1,420	1,923	2,277

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Table 1 presents summary statistics for the full sample and for each country using sample weights to represent the working-age population of 15-64 year olds. The 'Tasks' row indicates the share of workers in each country who perform the corresponding job activities at work.

3 Empirical Evidence

3.1 Descriptive Analysis

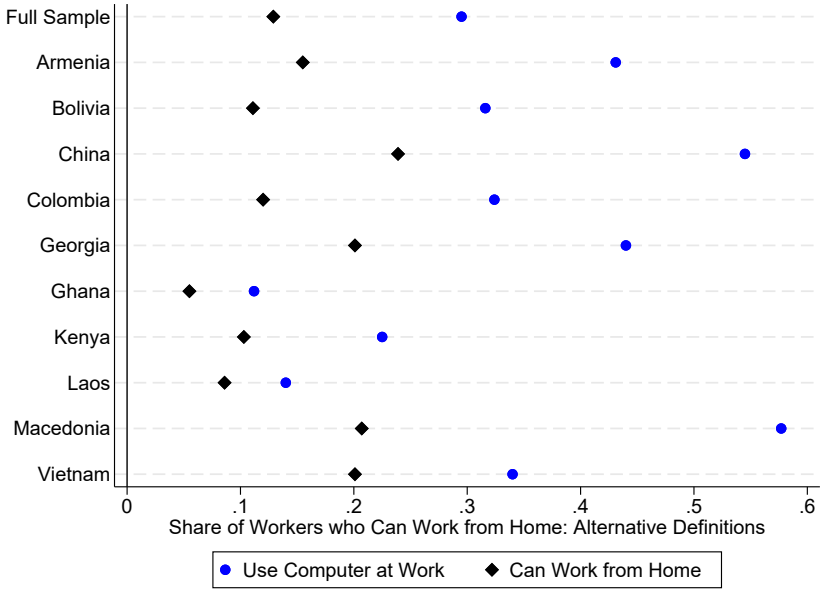
Figure 1 presents graphical evidence on the share of workers who use a computer at work and on those who can work from home across STEP countries. There is substantial heterogeneity in

[5] Summary statistics in the full sample are weighted by each country's population of 15-64 year olds. As such, these results give greater weight to countries with larger populations.

[6] While there is significant cross-country heterogeneity in these two measures, I remark that part of the difference in the informality share may be driven by its definition on the lack of pension benefits, which may vary across countries due to government policies (Maloney, 2004).

computer usage in the sample, as 58% of Macedonian workers report using a computer at work, compared to just 11% and 14% of workers in Ghana and Laos, respectively. The share of workers who could possibly work from home equals 12.9% in the full sample, which is far lower than the share of workers using computers due to additional task-based restrictions defined in Section 2. I similarly find important differences in the feasibility of working from home across countries, as 23% of workers in the Yunnan Province in China may do so, compared to just 5.5% of their counterparts in Ghana. All in all, the feasibility of working from home is strongly correlated with GDP per capita, as the correlation equals 0.684. As such, despite the conservative work-from-home definition adopted in this paper, the share of workers who may work from home in the STEP countries is far behind the corresponding share in the United States, which equals 34% (Dingel and Neiman, 2020). I further remark that since the STEP survey is representative of urban areas, the share of work which can be done from home in these countries is likely substantially lower, as agricultural employment is far more prevalent in rural areas.

Figure 1: Share of Jobs Which Can be Done from Home, by Country



Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure 1 presents the share of workers who use a computer at work as well as those who are defined to be able to work from home (Section 2) by country. Results are weighted using sample weights to represent the working-age population of 15-64 year olds.

In Table 2, I extend the analysis to consider heterogeneity in the share of individuals who can work from home across one-digit occupations.[7] Unsurprisingly, the feasibility of working from home is positively correlated with occupation-level wages. In the full sample, only 0.5% of plant and machine operators could potentially work from home, compared to 34.4% of workers in 'Professional' jobs. The feasibility of working from home for managers is not higher than for those in professional

[7] I present graphical evidence across three one-digit occupations in Figure A1.

occupations due to the prevalence of interactive tasks for managers. Interestingly, 41% of clerical occupations may be done from home, which follows from the lack of physical and interactive tasks involved in these jobs. Meanwhile, just 6.5% of workers employed in services and sales occupations may work from home.

There are important differences in the feasibility of working from home across countries in high-paying occupations. For instance, 14% of managers in Bolivia may do so, compared to 60% of their peers in Vietnam. Similarly, just 18% of professionals in Armenia can work from home, relative to 39% of their counterparts in Laos. Nonetheless, these differences are largely absent in lower-paying jobs, as at most 2.4% of machine operators are deemed to be able to work from home in STEP countries. Similar patterns emerge for workers in services/sales, crafts and trades and those in elementary occupations. Remarkably, work-from-home patterns at the one-digit occupation level are similar across all STEP countries. Dingel and Neiman (2020) document similar patterns in the United States, albeit with important differences in the prevalence of working from home. For instance, the authors document that 84% of jobs in management occupations can be performed at home in the U.S., compared to just 34% in the full STEP sample. As a result, this analysis further highlights that the economic costs from the pandemic in developing countries may far exceed those in the developed world.

Table 2: Share of Work-from-Home by One-Digit Occupation and Country

	All	Armenia	Bolivia	China	Colombia	Georgia	Ghana	Kenya	Laos	Macedonia	Vietnam
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Manager	0.34	0.316	0.142	0.237	0.338	0.339	0.281	0.349	0.298	0.388	0.604
Professional	0.344	0.177	0.283	0.374	0.325	0.271	0.223	0.317	0.39	0.334	0.523
Technician	0.274	0.228	0.271	0.378	0.132	0.303	0.272	0.357	0.372	0.314	0.463
Clerical	0.418	0.461	0.438	0.494	0.376	0.474	0.335	0.465	0.611	0.369	0.424
Services/Sales	0.064	0.042	0.044	0.128	0.103	0.092	0.008	0.023	0.029	0.131	0.086
Agricultural	0.001	0	0	0	0.	0	0	0	0.005	0.019	0
Craft/Trades	0.033	0.052	0.026	0.072	0.056	0.02	0.009	0.01	0	0.05	0.022
Machine Operators	0.005	0.024	0.001	0.005	0.006	0	0.005	0	0	0.011	0.005
Elementary Occupations	0.023	0.013	0.021	0.154	0.02	0.017	0	0.004	0	0.021	0.024

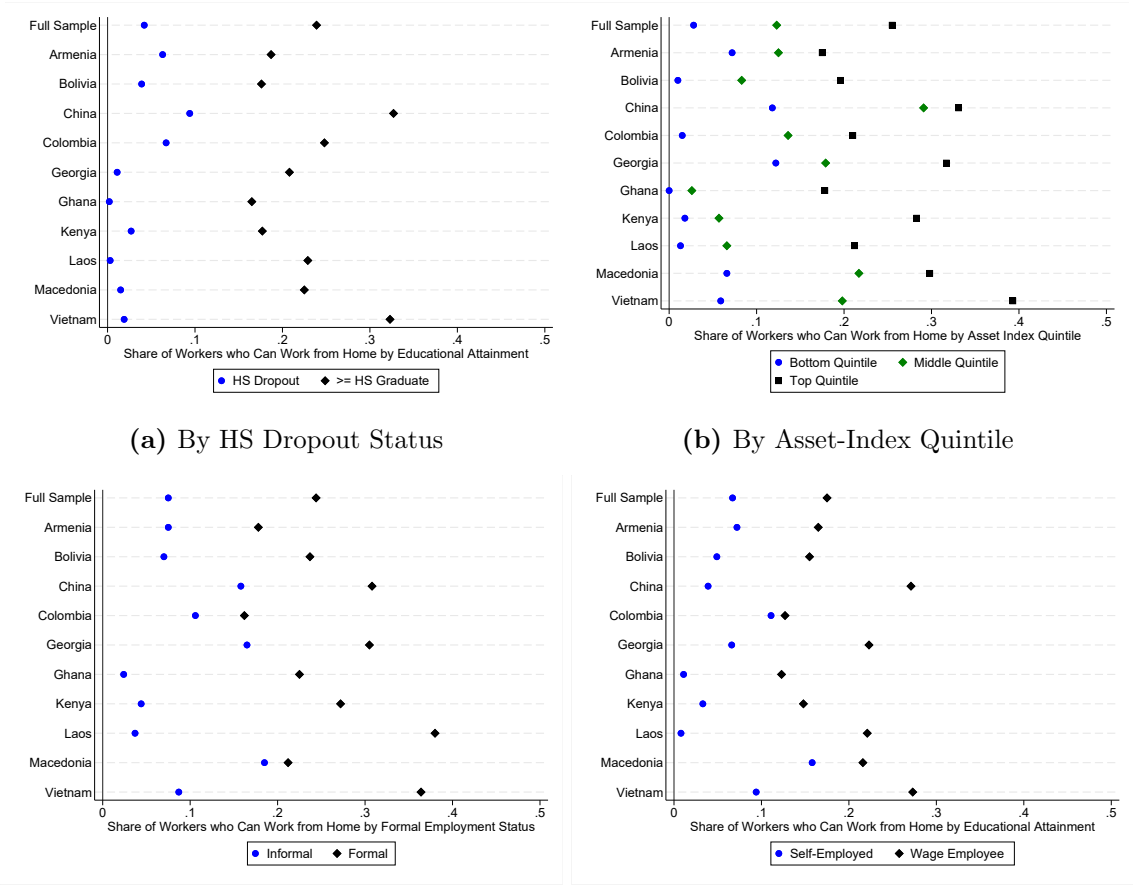
Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Table 2 presents evidence on the share of workers who can work from home by one-digit occupation and country. Results are weighted using sample weights to represent the working-age population of 15-64 year olds.

3.2 Characteristics of Work-from-Home Workers

Despite the low prevalence of work-from-home jobs in developing countries, examining the characteristics of individuals who cannot work from home can help governments to target policies towards particularly affected workers. In the first panel of Figure 2, I present evidence by educational attainment. In the full STEP sample, just 4.2% of high school dropouts are able to work from home, compared to almost 24% of their peers who at least completed a high school degree. Mongey and Weinberg (2020) similarly show that workers with less than a college degree in the U.S. are 33 percentage points more likely to work in a low work-from-home occupation vis-a-vis their more

educated peers. Educational differences in this dimension are present in all countries in the STEP sample — while 9.4% of high school dropouts in Yunnan can work from home, this share is far behind that of their more educated counterparts (exceeding 32%). In the second panel, I present heterogeneity across the within-country asset index distribution. The sample average shows that just 2.8% of households in the bottom quintile can work from home, far trailing their wealthier peers in the top quintile at 25.5%. While the top-bottom quintile asset gap in this measure exceeds 30 percentage points in Vietnam and equals 10 percentage points in Armenia, it is present in all countries in the sample.[8] As such, I remark the challenge facing governments in developing policies for helping households with limited access to self-insurance through their current assets.[9]

Figure 2: Characteristics of Work-From-Home Workers, by Country



(a) By HS Dropout Status

(b) By Asset-Index Quintile

(c) By Formal Employment Status

(d) By Self-Employment

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure 2 presents the share of jobs which can be done from home in the full sample and across STEP countries by workers'

[8] While Mongey and Weinberg (2020) do not directly observe information on households' assets, they find that workers below the median income are far more likely to work in low work-from-home occupations in the U.S.

[9] In Figure A2, I further show that males are less likely to be able to work from home than females, reaching 10.9% and 14.6% of the sample considered in the paper, respectively. Similarly, the feasibility of working from home for workers over 40 is lower (10.7%) than for their younger counterparts in STEP countries.

high school dropout status (Panel A), asset index quintile (Panel B), formal employment status (Panel C) and self-employment status (Panel D). Results are weighted using sample weights to represent the working-age population of 15-64 year olds.

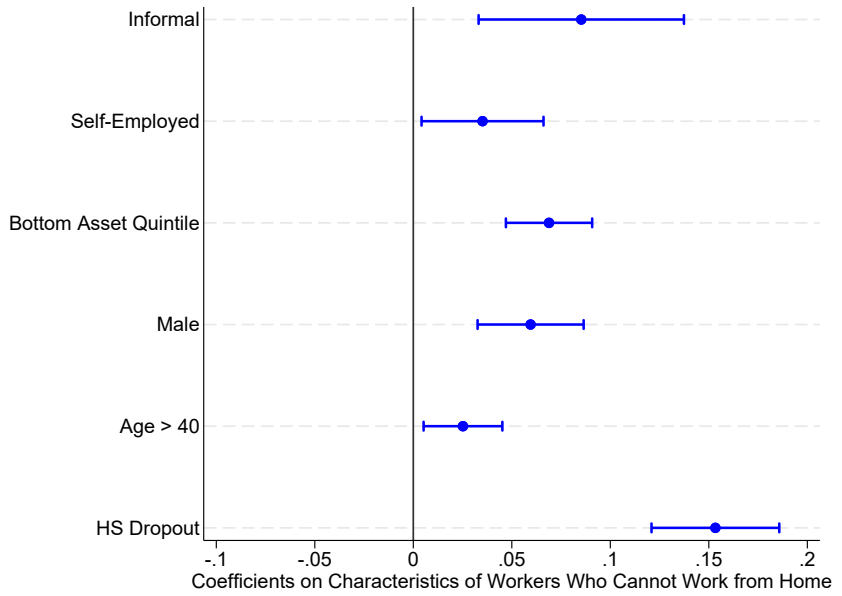
I additionally consider differences by employment outcomes. In Panel C, I show that just 7.5% of informal sector workers may carry on with their jobs at home, far below the corresponding share (24.4%) for their formal sector counterparts. This result holds across all countries, though the extent of the differences varies in magnitude. While the differences across self-employment status are smaller in magnitude (Panel D), the work-from-home gap is also present in this dimension across all STEP countries. To further understand which observed characteristics drive the relationships presented in Figure 2, I estimate the following OLS regression:

$$NWFH_{ij} = \beta_0 + \beta_1 \boldsymbol{X_i} + v_{ij} \tag{1}$$

where $NWFH_{ij}$ is a binary variable which equals 1 if worker i in occupation j **cannot** work from home and $\boldsymbol{X_i}$ includes binary variables measuring whether worker i is a high school dropout, male, older than 40, in the bottom asset quintile, self-employed, and/or in informal employment. I estimate equation (1) separately by country and also for the full sample, which includes country fixed effects.

In Figure 3, I present the results from equation (1). Fitting in with the evidence presented in Figure 2, the full sample results indicate that high school dropouts are 15.3 percentage points less likely to be able to work from home vis-a-vis their more educated peers, conditional on observed characteristics. Similarly, informality is associated with a lower likelihood of working from home by 8.5 percentage points, yet the estimated gap is about half as in the results from the bivariate regressions presented above. I further find that vulnerable groups are less likely to work from home, including workers older than 40, those in the bottom quintile of the asset distribution and self-employed individuals. I lastly find significant gender gaps in the feasibility of working from home, driven by the prevalence of physical tasks for males in developing countries. Mongey and Weinberg (2020) document similar gender differences in the United States.

Figure 3: Worker Characteristics Associated with **Not** Working from Home, Full Sample



Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure 3 presents the estimated coefficients from equation (1) for the full sample, including country fixed effects. Results are weighted using sample weights to represent the working-age population of 15-64 year olds. Standard errors clustered at the country level. 90% confidence intervals reported in solid lines.

In Table 3, I present results from equation (1) separately by country. The sign of the estimated coefficients largely follow the full sample results presented above, yet there are important cross-country differences. For instance, conditional on other observables, high school dropouts are 22 percentage points less likely to work from home than their more educated peers in Vietnam, yet the corresponding difference in Kenya equals 8 percentage points. The estimated work-from-home asset gap remains across all countries, yet it is not significant in Ghana and Laos. Similarly, while the gap across formal employment status remains in all countries (except for Macedonia), the difference is significant in just six countries in the sample. The cross-country heterogeneity in workers' capacity to work from home across observed characteristics highlights the importance of developing country-specific evidence regarding on the most vulnerable workers, to correctly design policies aimed at these workers.

As discussed above, by observing worker-level task information, I can further examine differences in workers' capacity to work from home *within* occupations in each country. To understand the role of occupations in determining the feasibility of working from home in developing countries, I re-estimate equation (1) including three-digit occupation fixed effects, which encompass 140 occupations. I present the estimated results for the full sample in Figure 4. The estimated signs on workers' observed characteristics directly follow the results presented in Figure 3, which indicate that high school dropouts, those in less wealthy households, males, older workers and self-

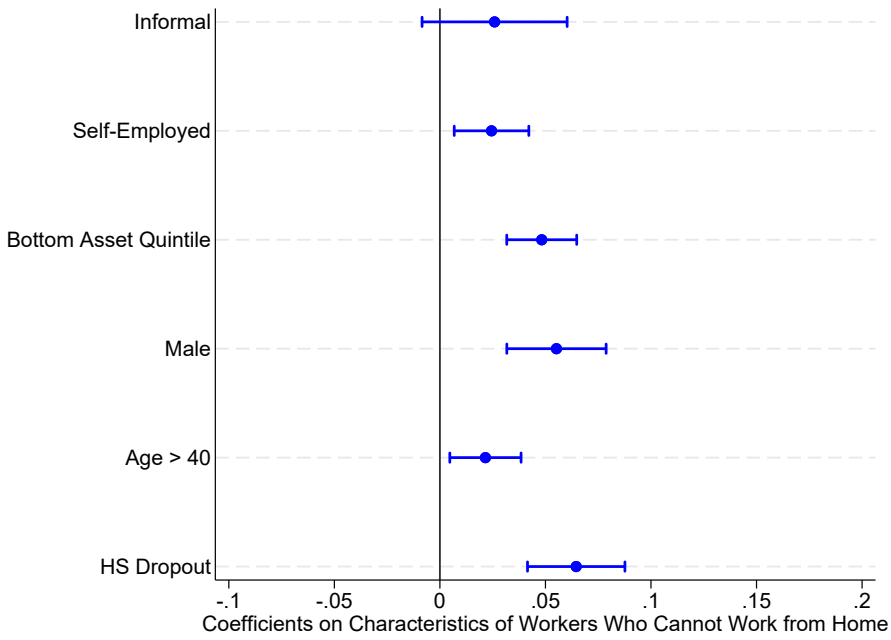
Table 3: Worker Characteristics Associated with **Not** Working from Home, By Country

	Armenia	Bolivia	China	Colombia	Georgia	Ghana	Kenya	Laos	Macedonia	Vietnam
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HS Dropout	0.103***	0.095***	0.162***	0.156***	0.182**	0.113***	0.083***	0.121***	0.170***	0.220***
	(0.028)	(0.015)	(0.027)	(0.018)	(0.074)	(0.012)	(0.013)	(0.016)	(0.035)	(0.018)
Age > 40	0.089***	-0.001	-0.004	0.044***	0.058**	0.005	-0.008	0.040***	0.017	0.067***
	(0.023)	(0.016)	(0.024)	(0.016)	(0.027)	(0.010)	(0.014)	(0.014)	(0.019)	(0.016)
Male	0.034	0.020	0.096***	0.078***	0.073***	0.006	0.015	0.020	0.072***	0.106***
	(0.023)	(0.015)	(0.023)	(0.016)	(0.028)	(0.010)	(0.012)	(0.014)	(0.019)	(0.016)
Bottom Asset Quintile	0.086***	0.083***	0.071**	0.097***	0.088**	0.013	0.064***	0.009	0.126***	0.085***
	(0.030)	(0.018)	(0.031)	(0.020)	(0.035)	(0.012)	(0.015)	(0.016)	(0.029)	(0.020)
Self-Employed	0.023	0.063***	0.172***	-0.009	0.103**	0.031**	0.046***	0.081***	0.059**	0.060***
	(0.045)	(0.017)	(0.035)	(0.020)	(0.041)	(0.012)	(0.013)	(0.017)	(0.030)	(0.019)
Informal	0.053	0.094***	0.036	0.034	0.097***	0.117***	0.170***	0.210***	-0.036	0.134***
	(0.038)	(0.020)	(0.026)	(0.021)	(0.029)	(0.016)	(0.016)	(0.023)	(0.031)	(0.020)
Observations	995	1691	1239	1695	927	2074	2327	1390	1806	2176
R^2	0.053	0.099	0.104	0.096	0.063	0.158	0.138	0.255	0.043	0.220

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table 3 presents the estimated coefficients from equation (1) separately for each country in the sample. Results are weighted using sample weights to represent the working-age population of 15-64 year olds.

employed workers are less likely to be able to work from home in the full sample. Nonetheless, the estimated coefficients are muted relative to the results presented above. For instance, within three-digit occupations, high school dropouts are 6.5 percentage points less likely to work from home vis-a-vis their more educated peers, yet the estimated coefficient is 60% lower than in the results from equation (1). Similarly, the estimated informality-work-from-home gap falls to 2.6 percentage points and is no longer statistically significant at the 10% level. As such, occupations partly explain the feasibility of working from home in developing countries, remarking their importance for structuring employment outcomes (Autor and Handel, 2013). Nonetheless, the remaining variation unaccounted by occupational characteristics highlights the importance of considering worker-level information in this context.

Figure 4: Within-Occupation Worker Characteristics Associated with **Not** Working from Home, Full Sample



Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure 4 presents the estimated coefficients from equation (1) for the full sample, including country fixed effects and three-digit occupation fixed effects. Results are weighted using sample weights to represent the working-age population of 15-64 year olds. Standard errors clustered at the country and three-digit occupation levels. 90% confidence intervals reported in solid lines.

In Table A1, I present the estimates from equation (1) with occupation fixed effects separately for each country. As with the results for the full sample, the estimated coefficients on workers' observed characteristics are significantly smaller and of varying statistical significance. Across all countries, high school dropouts are less likely to be able to work from home, and the coefficient remains significant in all but three countries in the sample. The relationship between household assets and work-from-home status remains negative across all countries even within occupations, yet the result is not significant in Georgia, Ghana and Laos. Lastly, within-occupation differences across formal employment status are similarly narrowed, as the coefficient is positive and significant in just two countries in the sample. All in all, these results indicate that more vulnerable workers are far less likely to continue working from home, thus likely suffering the worst labor market impacts from the pandemic. Since the estimated relationships vary across developing countries, identifying vulnerable workers and developing policies for correctly reaching them should be a priority for governments in these countries.

4 Conclusion

Social distancing and stay-at-home policies will play a critical role in stopping the spread of COVID-19. In this context, the negative employment impacts arising from the virus may be muted if workers are able to perform their jobs at home. In this paper, I have considered the feasibility of working from home in developing countries. As discussed above, measuring the number of jobs that can be done at home in these countries is challenging due to the lack of occupational dictionaries which map tasks to occupations. To overcome this limitation, I have relied on data from the World Bank's STEP survey, which has the advantage of measuring task content at the worker level across ten developing countries. The results presented in this paper indicate that a small share of workers in these countries may feasibly carry out their jobs from home, ranging from 6% in Ghana to 23% in Yunnan (China). Moreover, various vulnerable groups are more likely to suffer the negative consequences of the virus as their jobs cannot be done from home, including high school dropouts, informal workers and those in low-asset households. On the other hand, the extent of these relationships varies across countries, remarking the need for governments to identify vulnerable workers and create policies aimed at lessening the negative effects arising from COVID-19.

References

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.

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? *BFI White Paper, Becker Friedman Institute*.

Leibovici, F., A. M. Santacrue, and M. Famiglietti (2020). Social Distancing and Contact-Intensive Occupations. *Technical Report, St. Louis Federal Reserve Bank. On the Economy Blog*.

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.*

Maloney, W. F. (2004). Informality Revisited. *World Development 32*(7), 1159–1178.

Mas, A. and A. Pallais (2017). Valuing Alternative Work Arrangements. *American Economic Review 107*(12), 3722–59.

Mongey, S. and A. Weinberg (2020). Characteristics of Workers in Low Work-From-Home and High Personal-Proximity Occupations. *BFI White Paper, Becker Friedman Institute*.

Pierre, G., M. L. Sanchez Puerta, A. Valerio, and T. Rajadel (2014). STEP Skills Measurement Surveys: Innovative Tools for Assessing Skills.

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

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

Stinebrickner, T. R., R. Stinebrickner, and P. J. Sullivan (2018). Job Tasks and the Gender Wage Gap among College Graduates. Technical report, National Bureau of Economic Research.

Appendices

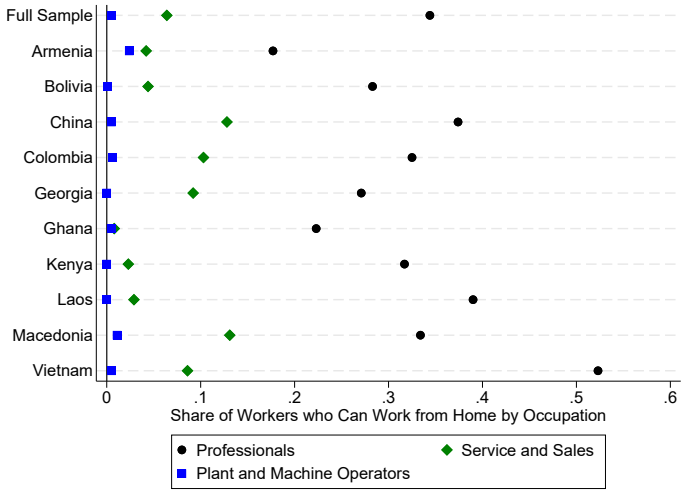
A Tables and Figures

Table A1: Within-Occupation Worker Characteristics Associated with **Not** Working from Home, By Country

	Armenia	Bolivia	China	Colombia	Georgia	Ghana	Kenya	Laos	Macedonia	Vietnam
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
HS Dropout	0.005	0.010	0.102***	0.072***	0.092**	0.031**	0.018	0.043**	0.040**	0.085***
	(0.027)	(0.015)	(0.034)	(0.023)	(0.042)	(0.012)	(0.015)	(0.018)	(0.018)	(0.016)
Age > 40	0.026	-0.003	-0.000	0.041*	0.040	0.002	-0.009	0.031	0.023	0.046***
	(0.023)	(0.020)	(0.027)	(0.024)	(0.037)	(0.009)	(0.012)	(0.022)	(0.021)	(0.018)
Male	0.009	0.020	0.080**	0.062***	0.110**	0.008	0.009	0.026	0.075**	0.076***
	(0.038)	(0.021)	(0.034)	(0.023)	(0.044)	(0.019)	(0.015)	(0.027)	(0.031)	(0.020)
Bottom Asset Quintile	0.087***	0.059***	0.070***	0.069***	0.051	0.009	0.032***	0.004	0.036**	0.040***
	(0.027)	(0.019)	(0.022)	(0.018)	(0.032)	(0.008)	(0.011)	(0.011)	(0.017)	(0.014)
Self-Employed	0.020	0.015	0.115***	0.009	0.071	0.030*	0.022*	0.084*	0.098**	-0.005
	(0.063)	(0.025)	(0.027)	(0.025)	(0.045)	(0.017)	(0.013)	(0.048)	(0.042)	(0.036)
Informal	0.025	-0.007	0.028	-0.014	0.047	0.047	0.080***	0.093	-0.085**	0.049*
	(0.045)	(0.033)	(0.020)	(0.026)	(0.039)	(0.042)	(0.030)	(0.075)	(0.038)	(0.028)
Observations	995	1691	1239	1695	927	2074	2327	1390	1806	2176
R^2	0.280	0.347	0.267	0.300	0.313	0.445	0.448	0.473	0.316	0.425

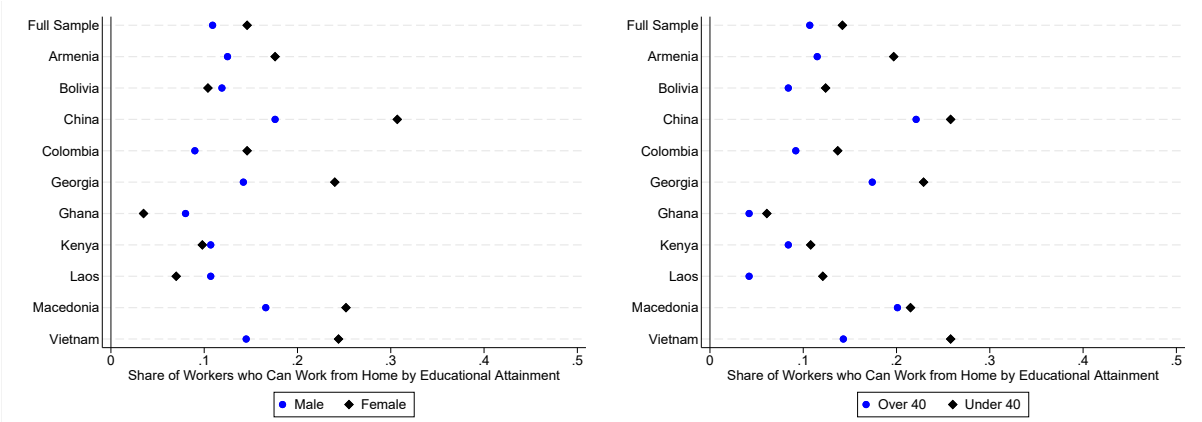
Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Standard errors in parentheses, clustered at the three-digit occupation level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table A1 presents the estimated coefficients from equation (1) with three-digit occupation fixed effects separately for each country in the sample. Results are weighted using sample weights to represent the working-age population of 15-64 year olds.

Figure A1: Share of Jobs Which Can be Done from Home by Occupation and Country



Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure A1 presents the share of workers in Professional, Service/Sales and Plant/Machine Operator occupations who are defined to be able to work from home by country. Results are weighted using sample weights to represent the working-age population of 15-64 year olds.

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



(a) By HS Dropout Status **(b)** By Age

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' gender (Panel A) and age (Panel B). Results are weighted using sample weights to represent the working-age population of 15-64 year olds.