Lockdown Accounting*†

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June 17, 2020

Abstract

We measure the effect of lockdown policies on employment and GDP across countries using individual- and sector-level data. Employment effects depend on the ability to work from home, which ranges from about half of total employment in rich countries to around 35% in poor countries. This gap reflects differences in occupational composition, self-employment levels, and individual characteristics across countries. GDP effects of lockdown policies also depend on countries' sectoral structure. Losses in poor countries are attenuated by their higher value-added share in essential sectors, notably agriculture. Overall, a realistic lockdown policy implies GDP losses of 20-25% on an annualized basis.

Keywords: Covid-19, work from home, structural change

JEL classification: O11, O14, J21

*We thank Joel Frischknecht and Joern Onken for outstanding research assistance. Research funding from Leverhulme, GFF Fund of the University of St. Gallen and ESRC-DFID (ES/L012499/1) is gratefully acknowledged. This paper supersedes "Working from home across countries" (Gottlieb, Grobovšek and Poschke, 2020) and "Who can work from home in developing countries" (Saltiel, 2020).

†Detailed data from the paper are available at `https://work-in-data.shinyapps.io/work_in_data/`. The website presents our measures of country-level WFH ability by detailed employment subgroups, and allows for downloads. It also contains a "lockdown simulator" that illustrates the effects of arbitrary sectoral lockdown policies (set by the user) by country.

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1 Introduction

Many countries are implementing social distancing and lockdown policies to tame the spread of Covid-19. These measures involve the closure of workplaces to limit interpersonal contact. They may remain in place in some form for a significant amount of time (Kissler et al., 2020). So far, 114 countries have implemented policies that require closing or work from home for all but essential workplaces (Hale et al., 2020). We measure the effect of such lockdowns on labor input and GDP for a large set of countries, with a focus on the determinants of their variation with country income per capita.

In sectors required to shutter workplaces, work can only be conducted from workers' homes. The ability to work from home (WFH) therefore is a key factor determining the economic consequences of social distancing policies. It has been measured for the United States (Dingel and Neiman, 2020) and for a set of European countries.[1] These studies have found that around 40% of jobs could potentially be carried out from home.[2] Evidence on the ability to work from home in poorer countries is more scant.[3] Yet, it is sorely needed, as poor countries are also implementing social distancing measures, often drastic ones.[4]

Lockdown policies by design affect different sectors differently: While some sectors are deemed essential and are permitted to remain open, non-essential sectors are closed down, in particular if their nature makes social distancing hard. The effects of sectoral lockdown policies have been evaluated for a few specific countries (in particular Fadinger et al. (2020) for Germany and Barrot et al. (2020) for France and a set of European countries), but little is known about their effect elsewhere, in particular in poorer countries.

Our paper addresses these issues, and makes two contributions. Our first contribution is to build a measure of WFH ability using individual-level data on job task content from countries across the income distribution, validate it, and analyze its variation with country income. To start, we show that individual WFH ability varies systematically by occupation, education, gender, and self-employment status, in similar ways across ten countries. We then show that a measure of WFH ability built using these individual characteristics strongly predicts the likelihood of remaining employed during the pandemic in the most recent survey data from the US and Peru.

Next, we compute a measure of WFH ability for 57 countries using harmonized individual-level data. We find that WFH ability is significantly lower in poor countries, both at the aggregate level and for many population subgroups. In a decomposition, we show that this is driven by differences in employment composition and demographics across countries: Workers in poor countries are more likely to be in occupations with low ability to WFH, they are more often self-employed, and they have lower levels of education, all of which are associated with lower WFH ability. Cross-country differences in WFH ability are thus closely associated with the systematic changes in the employment structure that occur with development (Gollin, 2008; Duernecker and Herrendorf, 2016).

[1] See e.g. Adams-Prassl et al. (2020), Barrot et al. (2020), Boeri et al. (2020), del Rio-Chanona et al. (2020), Fadinger et al. (2020), Koren and Pető (2020) and Mongey and Weinberg (2020).

[2] Bick et al. (2020) find that almost three quarters of workers in these jobs did in fact exclusively work from home in May 2020, when many US states were implementing lockdowns. This compares to only 8% of employees working from home full time in February 2020, with some more working from home part of the time. In line with this, Hensvik et al. (2020) find that in the US, the share of working hours performed from home in 2011 to 2018 is around 15%. Mas and Pallais (forthcoming) report a similar number. These numbers exhibit substantial variation across occupations.

[3] We build on Saltiel (2020), who first documented WFH ability for countries at various levels of development. More recently, Hatayama et al. (2020) consider two additional data sources.

[4] Twenty-two low- and lower-middle income countries have implemented lockdowns with a stringency index above 80 (corresponding to the 75^{th} percentile of the world distribution) (Hale et al., 2020).

Our second contribution consists in measuring the potential effects of four different lockdown policies on employment and GDP for 85 countries using a multi-sector model, the WFH ability measure, and disaggregated data from each country. In a decomposition, we show that while low WFH ability in poor countries implies a larger effect of lockdowns on their output and employment, their sectoral structure favors them: high employment and value added shares in sectors considered to be essential and therefore only marginally affected by lockdowns (in particular agriculture) cushion the effect of lockdowns. High income countries also have a favorable sectoral structure, with value added concentrated in high-end service sectors conducive to WFH. Middle-income countries, meanwhile, are disproportionately negatively affected by lockdowns, as their economic activity is centred on non-essential activities with low WFH ability. In other words, the effects of lockdowns are closely associated with structural change – the systematic changes in the sectoral structure of economies that occur with development (Kuznets, 1973; Gollin et al., 2002; Restuccia et al., 2008; Herrendorf et al., 2014; Duarte and Restuccia, 2019).

Beyond these contributions, our WFH measure has two advantages. First, it is built using data from countries of widely varying levels of income per capita, and not only one specific rich country. Second, the fact that it reflects variation of WFH ability across 72 detailed demographic groups implies that it can be used for the analysis of very fine-grained policies. It can thus serve as a valuable input in evaluating the costs of potential lockdown policies, in the quantitative analysis of lockdown and reopening policies, and in efforts to project the recovery.[5] Detailed data from the paper are available at `https://work-in-data.shinyapps.io/work_in_data/`. The website presents our measures of country-level WFH ability by detailed employment subgroups, and allows for downloads. It also contains a "lockdown simulator" that illustrates the effects of arbitrary sectoral lockdown policies (set by the user) by country.

The paper is structured as follows. In Section 2, we measure the ability to work from home at the individual level. In Section 3, we study how the share of work from home employment varies with country income per capita. In Section 4, we quantify the costs of lockdown policies on aggregate employment and GDP through the lens of a multi-sector model.

2 Measurement of the ability to work from home

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 respondents. We observe their age, gender and educational attainment, along with information on their labor market outcomes, including their current employment status and whether they have worked in the past twelve months. Furthermore, we observe whether they work as wage employees, in self-employment or in unpaid family work. We also observe workers' occupations under the harmonized ISCO-08 classification, along with measures of tasks they perform at work.[6,7]

[5] See e.g. Alon, Kim, Lagakos and VanVuren (2020); Alvarez et al. (2020); Farhi and Baqaee (2020); Brotherhood et al. (2020); Eichenbaum et al. (2020); Glover et al. (2020); Hall et al. (2020); Jones et al. (2020); Petrosky-Nadeau and Valletta (2020).

[6] STEP includes information on workers' sector of employment in four categories: agriculture, fishery and mining; manufacturing and construction; commerce; and other services.

[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.

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. 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. Since STEP covers countries whose GDP per capita ranges from $4,300 to upwards of $15,000, our measure represents an important input for cross-country comparisons.

Our preferred definition rules out working from home if a worker performs any of the following tasks at work: lifting anything heavier than 50 pounds, repairing/maintaining electronic equipment, operating heavy machinery or industrial equipment, or reporting they have a physically demanding job. Our definition also rules out work from home for those indicating that contact with customers is very important, unless they also report using e-mail for their job.

2.3 Determinants of the ability to work from home

In the first column of Table 1, we present average WFH feasibility across occupations. Overall, 45% of urban employment could be done remotely in the ten STEP countries.[8] The feasibility of WFH varies strongly across broad occupation groups. While the majority of jobs in managerial and professional occupations and in clerical support (groups 1-4) can be carried out from home, few jobs in elementary occupations, crafts, or occupations involving plant or machine operation (groups 6-9) can be done remotely.[9]

The ability to WFH varies not only with an individual's occupation, but also across other 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 20 percentage points. The estimated WFH shares are statistically different in all but two broad occupation groups (craft workers and elementary occupations). Similarly, the ability to WFH for wage employees (50%) is far higher than that for self-employed workers (35.3%). The difference is statistically significant for managers, technicians, services/sales workers and plant/machine operators. Lastly, women have a far higher ability to WFH (51.5%) than men (37.4%). These differences are significant in six of the nine broad occupation groups.

Table 1: Feasibility of working from home by definition and one-digit occupation

		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	0.655	0.682	0.450	0.731	0.561	0.690	0.634
Professionals	0.622	0.633	0.416	0.625	0.591	0.628	0.612
Technicians and Associate Professionals	0.585	0.620	0.398	0.601	0.476	0.634	0.542
Clerical Support Workers	0.691	0.716	0.574	0.694	0.634	0.739	0.608
Services and Sales Workers	0.385	0.425	0.350	0.427	0.346	0.385	0.383
Skilled Agricultural, Forestry and Fishery Workers	0.227	0.368	0.206	0.246	0.226	0.317	0.134
Craft and Related Trades Workers	0.304	0.294	0.311	0.277	0.331	0.518	0.172
Plant and Machine Operators, and Assemblers	0.250	0.286	0.210	0.271	0.188	0.444	0.204
Elementary Occupations	0.379	0.416	0.362	0.391	0.322	0.518	0.213
Sample Average	0.450	0.532	0.334	0.500	0.353	0.515	0.374
Observations	17598	10093	7505	11099	6499	9355	8243

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.

[8] Given our interest in developing a cross-country WFH measure, we rely on STEP data instead of O*NET. We present a direct comparison of task measures in the O*NET and STEP in Table A1. In Table A2, we report the estimated WFH employment share applying our preferred definition to the O*NET classification.

[9] We alternatively consider a measure in which we entirely rule out working from home unless workers report using e-mail at work. This reduces the overall WFH share to 8.8%, in line with Saltiel (2020).

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 the ability to WFH, we estimate the following regression:

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

where $\boldsymbol{X}_i$ represents a vector of worker i's observed characteristics, including educational attainment, age, gender and self-employment status; γ_o captures occupation fixed effects; λ_c denotes country fixed effects; and θ_k captures fixed effects for the four industries reported in STEP. Coefficient estimates shown in Table A3 indicate that higher-educated workers, women and wage employees are far more likely to work from home even within narrowly defined occupations, echoing the bivariate patterns reported in Table 1.[10]

To assess the relative importance of different determinants of the ability to work from home, we perform a variance decomposition. Workers' characteristics on their own account for 3-4% of the variance in the WFH measure, along with an additional 3-4% through the covariance with occupational categories. While one-digit occupational groups additionally account for 3.8% of the variance of the WFH measure, industries account for a negligible share (0.4%) of the variance (see Table A4 for full results).[11] The contribution of country fixed effects to the WFH variance is minor (1.6%), supporting our approach in Section 3, where we extend the STEP-based WFH measure to a much larger set of countries.

2.4 Validation

To assess the validity of our WFH measure as a predictor of employment, we take advantage of the April survey rounds of the *Encuesta Permanente de Empleo* (EPE) in Peru and the Current Population Survey in the US. Both surveys follow a rotating panel design, thus allowing us to observe workers' employment outcomes in their latest pre-Covid survey round.[12] We focus on individuals who were employed in the corresponding pre-Covid survey wave and examine whether they had a job in April 2020. We observe their initial occupation, industry and self-employment status, along with observed characteristics, such as gender, age and educational attainment.

For each worker in the Peru and US samples, we impute a predicted WFH score using the estimated coefficients from equation (1) for the STEP sample. We then examine the relationship between workers' predicted WFH feasibility and the likelihood they were employed in April, 2020. Our approach thus resembles Adams-Prassl et al. (2020) and Bick et al. (2020), yet provides novel evidence in a developing country. We control for workers' gender to account for disparities in labor market outcomes during Covid (Alon, Doepke, Olmstead-Rumsey and Tertilt, 2020), and for the essential nature of the sector, as WFH should be a stronger predictor of employment in non-essential industries.[13] Conditional on these two factors, an increase in the WFH score from 0 to 100 is associated with a 91 percentage point increased likelihood of remaining employed through April in the US, and 71pp in Peru. In the US, we further find that WFH ability is a stronger predictor of employment outcomes for workers in non-essential

[10] We do not find significant differences in WFH ability by age and thus ignore it in the rest of the analysis.

[11] Three-digit occupations explain a larger share of the variance of workers' WFH ability. Comparability across data sources requires us to focus on one-digit occupations in the rest of the paper.

[12] The structure of the EPE survey implies that April 2020 respondents were previously surveyed in April 2019. The 4-8-4 design in the CPS implies that we initially observe workers in different months in 2019 and early 2020. We do not use information from March 2020, as employment outcomes may have already been affected by the health shock.

[13] See Section 4.3 for information on essential sectors.

sectors, who could only work form home during lockdowns.[14] The strong association of our WFH measure with employment outcomes in countries as different as Peru and the US provides evidence of its predictive power, even beyond the STEP survey countries.

3 The ability to work from home across countries

In this section, we combine the measures of workers' ability to work from home from Section 2 with data on employment shares for detailed population subgroups for a wide range of countries to study how the ability to work from home varies across countries. In doing so, we narrow the analysis to urban employment, since urban areas are the focus of distancing policies as their higher population density provides favourable ground for the spread of contagious diseases (Alirol et al., 2011; Yang et al., 2015; Diop et al., 2020).

3.1 Data and measurement

We built a micro-dataset that contains information on labor market outcomes for 18 million working-age individuals across 57 countries ranging from Ethiopia to Luxembourg. To do so, we harmonized 617 country-year household and labor force surveys.[15] Beyond information on individual demographics, the dataset contains detailed information on workers' education, employment status, occupation, and sector of activity. In contrast to other sources of data on employment by sector or occupation, such as the International Labor Organization (ILO), our dataset contains individual level information and thus allows us to study employment at a highly disaggregated level.[16]

Section 2 shows that the ability to WFH varies significantly both across occupations, and with worker characteristics such as education, gender, and employment status. To account for these differences, we partition workers into 72 groups indexed by j, resulting from the full interaction of one-digit occupation (nine levels), education (high school graduates vs. dropout), gender, and employment status (self vs. wage employment). Denoting the share of type j workers that can work from home in the STEP data by η_j,[17] and the employment share of worker type j in country c by μ_{cj}, we measure the share of employment that can work from home in country c, h_c, as

$$h_c = \sum_j \mu_{cj} \eta_j. \tag{2}$$

We measure h_c for 57 countries and analyze how and why WFH ability of urban workers varies with country income.

3.2 Cross-country differences

Figure 1a provides a visual representation of the share of urban employment that can work from home by country income level. It reveals a large gap in WFH ability across country income groups: while in high-income countries, about half of urban employment can work from home,

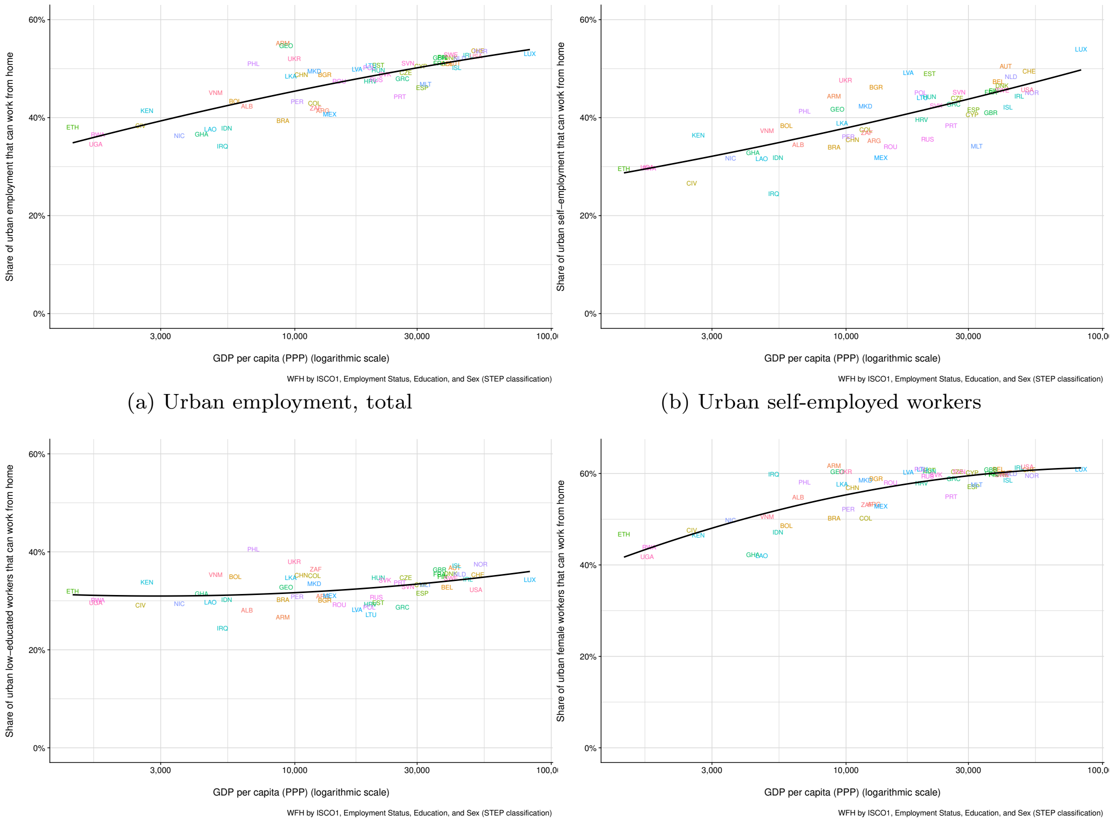
[14] We fail to find significant interactions of the essential nature of an industry and WFH scores in Peru. This may be explained by the strict lockdown put in place (Hale et al., 2020). See Table A5 for full results.

[15] Table A6 in Appendix A.2 provides an overview of data sources.

[16] At its highest level of detail, the ILO data on employment patterns in urban areas provides information along up to two dimensions: either occupation and sex, or economic activity and sex.

[17] Table A7 reports the values.

Figure 1: Ability to work from home of urban employment



(a) Urban employment, total

(b) Urban self-employed workers

(c) Urban low-skilled workers

(d) Urban female workers

Figures 1a, 1c, 1b and 1d use WFH ability measures that are occupation, employment status, sex and education specific. Their values are reported in Table A2.

only a third can do so in low-income countries. The income elasticity of the share of urban employment that can work from home amounts to 0.046.[18]

Our individual-level analysis of the ability to work from home in Section 2 highlights that three subgroups are less able to work from home: the self-employed, the low-skilled, and male workers. How does WFH ability of these subgroups differ across country income levels? Figure 1 shows that the WFH ability of female and self-employed workers is substantially lower in low-income countries compared to high-income countries, with a gap of 20 percentage points between WFH ability of these groups in the richest and the poorest countries. In contrast, WFH ability of low-skill workers does not vary systematically with country income per capita.

3.3 Sources of differences

Cross-country differences in the ability to work from home by construction reflect differences in employment composition, which differs systematically with development, given the well-known changes in the sectoral and occupational structure of economies with development (Gollin et al., 2002; Gollin, 2008; Herrendorf et al., 2014; Duernecker and Herrendorf, 2016; Duarte and Restuccia, 2019). In particular, a large share of urban workers in low-income countries are self-employed and pursue elementary occupations or work as service or sales workers. In fact, these two occupation groups account for over half of employment in low-income countries, while they amount to only one fifth of employment in high-income countries (Gottlieb et al., 2020).

[18]See Table A8 for full regression results and income elasticities for urban subgroups and aggregate employment.

Table 2: Decomposition of work from home employment by worker characteristics

Panel A: Work from home urban employment

	data WFH	counterfactual WFH				
quintile	(h_c)	occupation ($\hat{h}_c^o$)	employment type ($\hat{h}_c^s$)	gender ($\hat{h}_c^g$)	education ($\hat{h}_c^e$)	N
Q1	0.38	0.44	0.41	0.39	0.45	12
Q2	0.48	0.47	0.49	0.48	0.47	11
Q3	0.47	0.47	0.46	0.47	0.46	11
Q4	0.49	0.47	0.48	0.49	0.48	11
Q5	0.53	0.48	0.52	0.53	0.50	12

Panel B: Work from home employment

	data WFH	counterfactual WFH				
quintile	(h_c)	occupation ($\hat{h}_c^o$)	employment type ($\hat{h}_c^s$)	gender ($\hat{h}_c^g$)	education ($\hat{h}_c^e$)	N
Q1	0.35	0.42	0.39	0.35	0.43	12
Q2	0.47	0.45	0.47	0.46	0.45	11
Q3	0.45	0.45	0.44	0.45	0.43	11
Q4	0.47	0.45	0.46	0.47	0.46	11
Q5	0.51	0.46	0.50	0.51	0.48	12

Note: This Table reports the average work from home employment share h_c by quintiles of the income distribution. Columns (2)-(5) report the counterfactual work from home employment. For instance $\hat{h}_c^s$ is the counterfactual employment when the distribution of wage and self-employment is held constant across countries. The last column reports the sample size for each income group (N). Panel A reports the decomposition for urban employment, panel B reports the decomposition for total employment.

In contrast, the majority of urban employment in high-income countries is concentrated in managerial and professional occupations, which are more amenable to work from home. These jobs also are more likely to be carried out by workers with higher education and are also more likely to be done by females.

We next provide a quantitative assessment of the importance of these differences in the composition of urban employment. To do so, we compute, for each country, a counterfactual share of WFH employment that would prevail if its distribution of one characteristic is set to the cross-country average. We illustrate the calculation for the occupation distribution. We index the 8 combinations of attributes other than occupations by g. Let the employment distribution over occupations in country c be μ_{co}, and its average across all countries $\bar{\mu}_o$. To measure the importance of variation in the occupation distribution across countries, we compute a counterfactual WFH measure ($\hat{h}_c^o$) using the average occupation distribution:

$$\hat{h}_c^o = \sum_o \sum_g \mu_{cog} \frac{\bar{\mu}_o}{\mu_{co}} \eta_{og}, \qquad \bar{\mu}_o = \frac{1}{C} \sum_c \sum_g \mu_{cog} \tag{3}$$

where η_{og} is the share of WFH employment of workers in occupation o with characteristics g. We proceed analogously for employment status, education, and gender.

In Table 2, we report the counterfactual WFH employment levels by quintiles of the income per capita distribution for each of the worker characteristic we use to predict the WFH ability, namely occupation, employment status, education and gender.

Our decomposition shows that cross-country differences in the urban ability to WFH are largely driven by differences in occupation and educational attainment (see Panel A). Differences in employment status matter somewhat, while differences in gender composition play second fiddle. For instance, if the distribution of occupations were identical for all countries, the share of WFH employment would be on average 6 p.p. (=0.44-0.38) higher in the poorest quintile, and 5 p.p. lower (=0.53-0.48) in the richest quintile. By this metric, the variation in the occupation distribution on its own accounts for 73% (=1-(0.48-0.44)/(0.53-0.38)) of the interquintile difference in urban WFH ability.

The distribution of education also plays a major role. If it were common across countries, the WFH ability in countries of the lowest quintile would be 7 p.p. higher, while it would be 3 p.p. lower in countries in the highest quintile. On its own, the distribution of education thus explains 67% of the interquintile difference.

Hence, differences in WFH ability across country-income levels are largely driven by differences in the distribution of occupations and individual characteristics, in particular educational attainment. These findings are similar at the country level (see Panel B).

4 Sectoral lockdown policies

In this section, we evaluate the impact of various sectoral lockdown policies on aggregate effective employment and GDP for 85 countries across the income per capita distribution. These effects will depend on a country's WFH ability, but also on its industrial structure, since lockdown policies are typically specified on a sectoral level.

4.1 Model description

We use a multi-sector model to simulate the effects of lockdowns. We assume that following a lockdown, the ratio of effective employment relative to trend in country c equals

$$n^c = \sum_{i=1}^{I} n_i^c \mu_i^c = \sum_{i=1}^{I} \left[1 - \lambda_i \left(1 - h_i^c\right)\right] \mu_i^c = \underbrace{\sum_{i=1}^{I} \left(1 - \lambda_i\right) \mu_i^c}_{\equiv n_w^c} + \underbrace{\sum_{i=1}^{I} \lambda_i h_i^c \mu_i^c}_{\equiv n_h^c} \tag{4}$$

where n_i^c is the level of employment in sector i relative to trend and μ_i^c the pre-shock employment share of sector i. We posit that the lockdown policy shuts down a fraction $\lambda_i \in [0, 1]$ of workplaces in sector i. Locked down employment can be substituted at the rate $h_i^c \in [0, 1]$, the share of WFH employment in sector i. Implicitly, we assume that work from home is as efficient as regular work. The last equality of (4) separates effective labor into regular work, n_w^c, and aggregate work from home, n_h^c. In the absence of lockdowns, $n^c = n_w^c = 1$ and $n_h^c = 0$.

GDP relative to trend is given by

$$y^c = \prod_{i=1}^{I} \left(n_i^c\right)^{\nu_i^c} = \prod_{i=1}^{I} \left[1 - \lambda_i \left(1 - h_i^c\right)\right]^{\nu_i^c} \tag{5}$$

where $\nu_i^c \in [0, 1]$ is the nominal value added share of sector i, $\sum_i \nu_i^c = 1$. In Appendix A.3, we show how to derive equation (5) from a model featuring intersectoral trade in intermediate inputs. The central assumption is that labor and capital, post-shock, cannot move across sectors and that the sectoral drop in capital utilization is proportional to that of labor.[19,20] Simulation results describe employment and GDP changes relative to trend while a lockdown policy is in

[19]Our analysis abstracts from factors other than the lockdown that affect employment and output. Such factors could be, among others, reductions in labor supply (voluntary or for health reasons), financial frictions, or frictions in final or intermediate goods markets. The model does, however, capture adjustments in the demand and supply of final and intermediate goods under the conditions spelled out in Appendix A.3.

[20]Fadinger et al. (2020) use a similar approach, with the difference that capital utilization does not change. The model in Barrot et al. (2020) features non-unitary elasticities of substitution both between intermediate inputs and between final goods, while capital utilization is implicitly proportional to labor.

place. Hence, ignoring dynamic adjustments, the change in annual GDP with a two-month lockdown would be one-sixth of the reported change.

4.2 Data and measurement

We define sectors according to the one-digit ISIC classification. Country-specific sectoral value added shares ν_i^c are obtained from the United Nations Statistics Division and the World Input Output Database.[21]

We construct the country-sector-specific WFH rate h_i^c by combining the WFH ability computed in the STEP data and employment shares by one-digit ISIC sector and one-digit ISCO occupation from ILO.[22] We use the ILO data rather than the harmonized micro dataset employed in Section 3 in order to maximize country coverage. The downside is that the ILO data do not allow to use the full heterogeneity of WFH ability presented in Table A7, but only variation across occupations and sectors. Thus, we compute the WFH ability by occupation o and broad sector b, $\eta_{o,b}$.[23] Then, $h_i^c = \sum_o \mu_{oi}^c \eta_{ob}$, $\forall i \in b$, where μ_{oi}^c is the employment share of occupation o in sector i. In total, we can measure ν_i^c and h_i^c for 85 countries.

4.3 Lockdown policies

We study four lockdown policies. In the first "complete" lockdown policy, workplaces in all sectors are shut down: $\lambda_i = 1$, $\forall i$. In this case, the fraction of aggregate effective labor coincides with the aggregate WFH rate, namely $n^c = \sum_{i=1}^{I} h_i^c \mu_i^c$. In the second "non-agricultural" lockdown policy, all sectors are shut down with the exception of agriculture. This policy fleshes out the importance of a sector considered to be essential in most countries and therefore allowed to operate normally. The third and fourth lockdown scenarios replicate policies actually in place. The "hard" lockdown leaves open a limited number of essential sectors, $\lambda_i = 0$, closes down non-essential sectors, $\lambda_i = 1$, and partially shuts down workplaces in other sectors, $\lambda_i \in (0, 1)$. We construct λ_i using the index of essential sectors assembled by Fana et al. (2020), who document activities exempt from the strict March 2020 lockdown decrees in Germany, Italy, and Spain.[24] Finally, we consider a "soft" lockdown policy, designed to capture the situation as shutdowns are eased. We define it as lifting three-quarters of the employment restrictions in agriculture and industry, and half the restrictions in services. The latter are being lifted more slowly as they involve more interpersonal interaction, which fosters the risk of virus transmission. This leaves substantial restrictions in sectors such as accommodation and food services, education, and arts, entertainment and recreation. Appendix A.4 summarizes our approach and presents the values for λ_i under each policy.

4.4 Results

Figure 2 plots aggregate effective employment and GDP relative to trend against countries' income level. The top panes portray the complete lockdown. Here, the aggregate employment

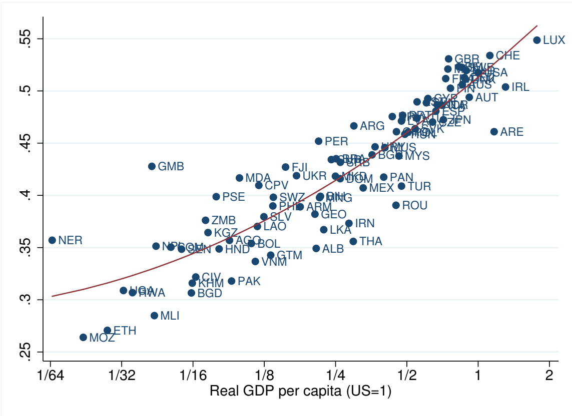
[21]For each country, we consider the most recent observation over the period 2010-2019. Whenever possible, we follow the ISIC Revision 4 classification. For a few countries, we use the ISIC Revision 3.1 classification and impute the missing data.

[22]For each country, we consider the most recent observation over the period 2010-2019. In most countries, including poor ones, the data are from 2017.

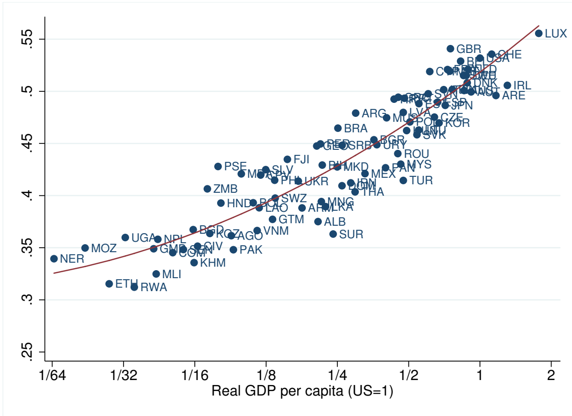
[23]The broad sectors are agriculture, fishing and mining; manufacturing, construction and transportation; commerce; and other services. Figures shown in Table A9.

[24]Lockdown policies were similar in North American jurisdictions, like the State of New York in the US and Ontario and Québec in Canada.

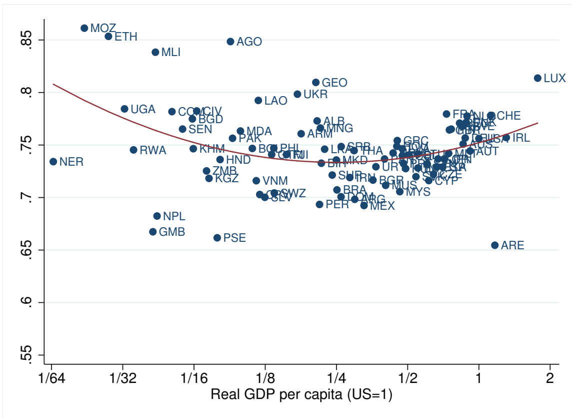
Figure 2: Effective employment and GDP relative to trend under complete and hard lockdowns



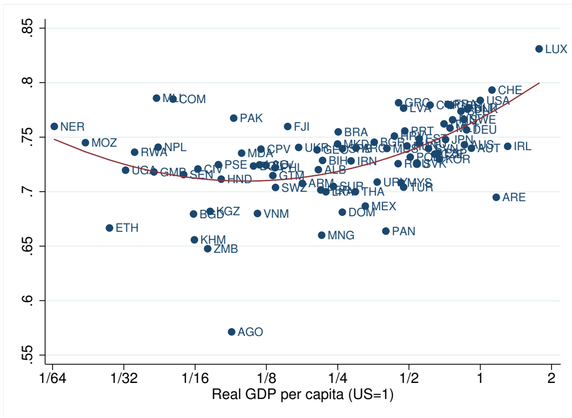
(a) Employment, complete lockdown



(b) GDP, complete lockdown



(c) Employment, hard lockdown



(d) GDP, hard lockdown

Real GDP per capita of each country corresponds to the 2017 PPP-adjusted series from Feenstra et al. (2015), normalized to the U.S. The trend line is a quadratic fit of the logarithm of real GDP per capita.

decline corresponds to the fraction of aggregate employment that cannot work from home. Employment declines most in poorer countries, which have a lower aggregate WFH capacity. The change in GDP mirrors this pattern. The bottom panes portray the hard lockdown. Strikingly, for this realistic policy, effective employment and GDP no longer increase in income. Rather, they exhibit a U-shape. Figure A1 shows that results are similar for the non-agricultural and soft lockdowns.

Table 3 presents the effect of each lockdown policy by quintile of the distribution of country income per capita. The first two columns show, for each quintile, average GDP and employment. Columns (3) and (4) disaggregate employment into the regular and work from home components. Under the complete lockdown, employment drops to 33.6% of its pre-shock level in the poorest quintile, compared to 50.8% in the richest quintile. Put differently, the aggregate WFH capacity is roughly one-third in poor countries and one-half in rich countries. This is in line with the results presented in Section 3.

The pattern of employment by country income level is completely reversed under the non-agricultural lockdown policy: in this scenario, employment declines least in the poorest countries, due to their high employment shares in agriculture (shown in column 3). GDP declines more than employment, in particular in the poorest countries. This is because the agricul-

Table 3: Average impact of lockdown policies on country income groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Complete lockdown						
	y	n	n_w	n_h	G	H	V
Q1	0.356	0.335	0.000	0.335	-0.192	-0.077	-0.114
Q2	0.401	0.382	0.000	0.382	-0.070	-0.032	-0.039
Q3	0.432	0.419	0.000	0.419	0.002	-0.009	0.011
Q4	0.473	0.465	0.000	0.465	0.096	0.040	0.056
Q5	0.517	0.511	0.000	0.511	0.184	0.083	0.101
	Non-agricultural lockdown						
	y	n	n_w	n_h	G	H	V
Q1	0.508	0.631	0.377	0.254	0.018	-0.066	0.084
Q2	0.488	0.589	0.265	0.324	-0.019	-0.026	0.007
Q3	0.478	0.522	0.132	0.390	-0.039	-0.009	-0.030
Q4	0.499	0.520	0.073	0.448	0.004	0.038	-0.034
Q5	0.526	0.527	0.021	0.506	0.058	0.079	-0.021
	Hard lockdown						
	y	n	n_w	n_h	G	H	V
Q1	0.717	0.756	0.597	0.159	-0.016	-0.025	0.009
Q2	0.716	0.753	0.572	0.181	-0.018	-0.011	-0.007
Q3	0.716	0.726	0.518	0.209	-0.017	-0.003	-0.014
Q4	0.743	0.732	0.497	0.235	0.020	0.014	0.006
Q5	0.765	0.758	0.516	0.242	0.049	0.033	0.016
	Soft lockdown						
	y	n	n_w	n_h	G	H	V
Q1	0.909	0.908	0.841	0.067	-0.002	-0.005	0.003
Q2	0.910	0.905	0.828	0.078	-0.001	-0.002	0.001
Q3	0.908	0.895	0.807	0.088	-0.003	-0.001	-0.002
Q4	0.912	0.897	0.799	0.098	0.001	0.003	-0.001
Q5	0.917	0.902	0.798	0.104	0.007	0.006	0.000

Note: The results indicate averages over quintiles of countries ordered by real GDP per capita in 2017. Each bin consists of 17 countries. Average empirical GDP per capita expressed relative to the U.S. equals 0.05 in Q1, 0.14 in Q2, 0.30 in Q3, 0.55 in Q4, and 0.95 in Q5. The terms G, H and V are as defined in equation (6).

tural employment share generally exceeds the sector's value added share (Restuccia et al., 2008; Gollin et al., 2014; Herrendorf and Schoellman, 2015). The largest declines in employment and and value added now occur in middle-income countries.

This pattern is preserved under the realistic hard lockdown scenario, as also seen in Figure 2. Here, employment declines by 20 to 30%, with the largest declines in middle-income countries.[25] Although poorer countries have the lowest ability to WFH, their employment share in essential sectors is highest. As a result, they maintain larger regular employment n_w, and their total employment n is comparable to the richest countries, despite lower WFH ability.[26] This pattern is entirely driven by the large agricultural employment share in poor countries. Since the value added share of agriculture in poor countries falls short of its employment share, output losses significantly exceed employment in the poorest countries, and are similar to those in middle-income countries. Results are qualitatively similar for the soft lockdown scenario.

[25] Model-implied employment reductions in the hard lockdown policy are close to those observed during the pandemic. For instance, US employment declined by 20% from February to April 2020 according to CPS data (Bick and Blandin, 2020).

[26] On average, WFH ability does not differ significantly between essential and non-essential sectors (Figure A2).

4.5 Sources of output changes: a decomposition

The results in Table 3 show that the effects of a lockdown policy in a particular country reflect not only the ability to work from home, but also the sectoral structure of its economy. We now assess the quantitative importance of these two components.

Let $\overline{y}$ be the GDP ratio for a reference economy with average value added shares and work from home rates across the sample of countries, $\overline{\nu}_i = \frac{1}{C}\sum_{c=1}^{C} \nu_i^c$, $\overline{h}_i = \frac{1}{C}\sum_{c=1}^{C} h_i^c$. Then, the log of the GDP ratio y^c for any country c relative to the reference economy can be decomposed as

$$\underbrace{\ln y^c - \ln \overline{y}}_{\equiv G^c} = \underbrace{\sum_{i=1}^{I}\left(\frac{\nu_i^c + \overline{\nu}_i}{2}\right)(\ln n_i^c - \ln \overline{n}_i)}_{\equiv H^c} + \underbrace{\sum_{i=1}^{I}\left(\frac{\ln n_i^c + \ln \overline{n}_i}{2}\right)(\nu_i^c - \overline{\nu}_i)}_{\equiv V^c}, \tag{6}$$

where

$$H^c \approx \sum_{i=1}^{I}\left(\frac{\nu_i^c + \overline{\nu}_i}{2}\right)\lambda_i\left(h_i^c - \overline{h}_i\right), \qquad V^c \approx \sum_{i=1}^{I}\lambda_i\left(\frac{h_i^c + \overline{h}_i}{2} - 1\right)(\nu_i^c - \overline{\nu}_i).$$

The term H^c captures the (value added-weighted) effect of differences in WFH ability, which affect effective sectoral employment. The term V^c captures the effect of differences in the weight of sectors across countries. A country thus experiences a small GDP drop relative to an "average" economy if it exercises relatively more work from home ($H^c > 0$), if it has a relatively high value-added share in sectors maintaining high employment ($V^c > 0$), or both. Our decomposition separates these factors.

We find that under the hard (soft) lockdown, the variance of V^c accounts for 80.6% (91.0%) of the variance of G^c, compared to 18.8% (22.8%) for the variance in H^c. The share explained by the covariance term is small. Hence, in the full cross-section of countries, sectoral structure is the main determinant of the effect of lockdowns on GDP.

The role of H and V differs systematically across country income groups. Columns (5)-(7) of Table 3 present the average G, H, and V by quintile. Under complete lockdown, both H and V contribute to the fact that GDP declines more steeply in poorer countries. GDP in poor countries drops disproportionately both because they have a lower WFH capacity *and* because their value added is concentrated in sectors where employment – due to low average WFH capacity – is affected most severely. Under the non-agricultural lockdown scenario, the two forces work in opposite directions. While their low WFH capacity, captured by H, still contributes negatively to the relative GDP of poor countries, their high value added share in agriculture, captured by V, more than compensates.

This pattern remains under the realistic hard lockdown policy. Here, the larger value added share of the poorest countries in essential sectors, captured by V, eliminates about a third of their lower WFH ability, captured by H. Lower-middle income countries suffer output losses roughly as large as the poorest countries. Although they have higher WFH ability, they are penalized by their sectoral structure, with high value added shares in sectors with low WFH ability. In countries in the third quintile of the income distribution, the sectoral composition accounts for over 80% of GDP losses compared to the reference economy. The richest countries, in contrast, benefit from both the highest WFH ability and a favorable sectoral structure, with relatively large value added shares in sectors with high WFH ability. Their sectoral structure is responsible for about a third of their lower GDP loss compared to the reference economy. This is similar, to a lesser extent, for countries in the fourth quintile of the income distribution.

The same pattern arises for the soft lockdown policy. However, all effects are weaker, and countries over the whole income spectrum experience a similar-sized drop in GDP. These patterns are visualized in Figure A3.

5 Conclusion

This paper measures the costs of lockdown policies on employment and GDP for low, middle and high-income countries. The ability to work from home and a country's sectoral composition are two key variables that determine these costs. We provide a novel measure of the ability to WFH and use a multi-sector model to measure these costs. Our results show that lockdown policies affect middle-income countries most, while low-income and high-income countries are less affected. Looking forward, more work is needed to further understand the essential nature of sectors to think about the optimal design of sectoral lockdown policies.

Our study provides valuable numbers for the study of the effects of recent lockdown policies across the world. The measures of WFH ability we compute should be useful to inform others' projections of costs from lockdowns. For ease of access, we provide a "lockdown simulator" that allows simulating the effect of arbitrary sectoral lockdowns policies.[27]

[27] Accessible at https://work-in-data.shinyapps.io/work_in_data/.

A Appendix

A.1 Appendix tables and figures

Table A1: Work from home measurement

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	Handling and Moving Objects is very important (4.0+ of 5)	
3	Controlling Machines and Processes [not computers nor vehicles] 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? Binary response.
4	Operating Vehicles, Mechanized Devices, or Equipment is very important (4.0+ of 5)	
5	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.
6	Repairing and Maintaining Mechanical Equipment is very important (4.0+ of 5)	As part of this work, do you (did you) repair/maintain electronic equipment? Binary response.
7	Repairing and Maintaining Electronic Equipment is very important (4.0+ of 5)	
8	Inspecting Equipment, Structures, or Materials is very important (4.0+ of 5)	
Section	*Generalized work activities*	
9	"Average respondent says they use email less than once per month"	Does your work require the use of the following [e-mail]? Binary response.
10		As a part of your work do you (did you) use a computer? Binary response.

Note: The questions in the STEP column are taken from this questionnaire. The questions from the O*NET classification used Dingel and Neiman (2020) are taken from their codes, in particular from the file `onet_characteristics.do`.

Table A2: Feasibility of working from home by definition and one-digit occupation

	Occupation, ISCO One Digit	O*NET - DN(2020)	O*NET	STEP
1	Managers	70.0	82.2	65.5
2	Professionals	69.8	78.2	62.2
3	Technicians and Associate Professionals	37.0	53.4	58.5
4	Clerical Support Workers	53.4	59.2	69.1
5	Services and Sales Workers	15.8	30.6	38.5
6	Skilled Agricultural, Forestry and Fishery Workers	3.3	31.3	22.7
7	Craft and Related Trades Workers	4.9	15.0	30.4
8	Plant and Machine Operators and Assemblers	0.5	3.0	25.0
9	Elementary Occupations	6.8	15.7	37.9
	Average	41.6	53.8	45.0

Note: Column 1 reports the share of employment that can work from home using the work from home classification proposed by Dingel and Neiman (2020) using O*NET data. Column 2 reports the share of employment that can work from home using a work from home classification based on STEP questionnaires, applied to O*NET data. Column 3 reports the share of employment that can work from home using the work from home classification based on STEP questionnaires, using STEP data. The exact questionnaire questions used to construct these classifications are reported in Table A1.

Table A3: Determinants of working from home: observables and occupations

	(1)	(2)	(3)
HS Graduate	0.173	0.077	0.068
	(0.027)	(0.026)	(0.028)
Age $<$ 40	-0.003	-0.005	0.002
	(0.015)	(0.021)	(0.015)
Male	-0.156	-0.134	-0.113
	(0.020)	(0.054)	(0.022)
Wage Employment	0.106	0.065	0.044
	(0.024)	(0.029)	(0.023)
Occupation FE	None	One-Digit	Three-Digit
R^2	0.083	0.125	0.182
Observations		17,598	

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Standard errors in parentheses. Table A3 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.

Table A4: Variance decomposition of working from home: share explained by different factors

% Explained	(1)	(2)
Variance	1.000	1.000
$Var(X_i)$	0.042	0.030
$Var(\gamma_O)$	0.038	0.100
$Var(\lambda_c)$	0.016	0.014
$Var(\theta_k)$	0.004	0.002
$Cov(X_i, \gamma_O)$	0.034	0.041
$Cov(X_i, \lambda_c)$	-0.006	-0.004
$Cov(X_i, \theta_k)$	0.009	0.004
$Cov(\gamma_O, \lambda_c)$	-0.004	-0.003
$Cov(\gamma_O, \theta_k)$	0.008	0.007
$Cov(\theta_k, \lambda_c)$	-0.002	-0.001
$Var(\varepsilon_{iock})$	0.864	0.813
R^2	0.136	0.187
Occ FE	One-Digit	Three-Digit
Observations	16,299	

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Table A4 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 A5: WFH validation exercise: evidence for USA and Peru

	USA			Peru		
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted WFH Score	0.397	0.809	0.918	0.427	0.671	0.712
	(0.017)	(0.021)	(0.031)	(0.079)	(0.094)	(0.137)
Male		0.210	0.206		0.140	0.135
		(0.006)	(0.006)		(0.030)	(0.030)
Industry Emp. (% Carried Out)			0.352			0.171
			(0.027)			(0.093)
Interaction: WFH × Industry			-0.366			0.004
			(0.046)			(0.194)
Constant	0.527	0.198	0.067	0.032	-0.156	-0.247
	(0.009)	(0.013)	(0.018)	(0.037)	(0.055)	(0.074)
Observations	28442	28442	28442	1060	1060	1060
R^2	0.020	0.055	0.072	0.027	0.046	0.068

Source: Skills Toward Employability and Productivity (STEP) Survey, Current Population Survey (USA) and *Encuesta Permanente de Empleo* (Peru).
Note: Standard errors in parentheses. Table A5 presents evidence on the relationship between predicted WFH scores, gender and the essential nature of sectors on employment outcomes in April, 2020 in USA and Peru. WFH scores are predicted using the estimated coefficients from a modified version of equation (1) (without industry and country fixed effects). Industry employment shares during lockdowns follow from Fana et al. (2020), as described in Section 2.2. Results are weighted using sample weights in each country.

Table A6: Individual level dataset. Information on data sources, sample size and country years covered.

Name	Years	Sample size (in thds)	GDP per capita (PPP)	Source
Albania	2002–2012	22	4'845–9'918	LSMS
Argentina	2004–2006	114	12'074–13'770	LFS
Armenia	2013–2013	1	8'979–8'979	STEP
Austria	1999–2017	951	34'938–51'524	LFS
Belgium	1999–2017	456	32'357–46'522	LFS
Bolivia	2012–2012	1	5'860–5'860	STEP
Brazil	2002–2006	628	8'358–9'515	LFS
Bulgaria	1995–2017	301	6'390–20'027	LSMS, LFS
China	2012–2012	1	10'596–10'596	STEP
Colombia	2012–2012	1	11'934–11'934	STEP
Cote d'Ivoire	1985–1988	4	2'429–2'734	LSMS
Croatia	2002–2017	151	13'750–24'368	LFS
Cyprus	1999–2017	197	25'255–36'137	LFS
Czech Republic	1999–2017	720	20'059–36'061	LFS
Denmark	1999–2017	383	33'525–49'607	LFS
Estonia	1999–2017	109	10'772–31'013	LFS
Ethiopia	2013–2014	40	1'248–1'357	LFS, UES
Finland	1999–2017	183	31'433–42'902	LFS
France	2003–2017	804	31'567–40'975	LFS
Georgia	2013–2013	1	9'254–9'254	STEP
Ghana	2005–2017	68	3'007–5'154	LSMS, STEP, LFS
Greece	1999–2017	1'093	22'683–31'340	LFS
Hungary	1999–2017	1'206	14'380–27'531	LFS
Iceland	1999–2017	76	37'628–51'970	LFS
Indonesia	1993–2014	52	3'811–9'710	ILFS
Iraq	2006–2006	26	5'223–5'223	LSMS
Ireland	1999–2017	973	33'680–73'297	LFS
Kenya	2013–2013	2	2'652–2'652	STEP
Lao People's Democratic Republic	2012–2012	2	4'693–4'693	STEP
Latvia	1999–2017	157	9'655–26'643	LFS
Lithuania	1999–2017	264	10'373–30'936	LFS
Luxembourg	1999–2017	157	64'436–99'477	LFS
Macedonia, The Former Yugoslav Republic of	2013–2013	1	11'910–11'910	STEP
Malta	2009–2017	71	26'792–41'847	LFS
Mexico	2005–2005	149	13'691–13'691	LFS
Netherlands	1999–2017	692	37'786–50'024	LFS
Nicaragua	2005–2005	10	3'548–3'548	LSMS
Norway	1999–2017	193	37'645–63'768	LFS
Peru	2009–2014	114	8'515–11'086	LFS
Philippines	2015–2015	1	6'896–6'896	STEP
Poland	1999–2017	1'231	13'114–28'420	LFS
Portugal	1999–2017	718	22'413–28'567	LFS
Romania	1999–2017	1'113	7'441–25'262	LFS
Russian Federation	2004–2015	80	12'554–25'777	RLMS-HSE
Rwanda	2013–2016	24	1'551–1'872	LFS
Slovakia	1999–2017	482	14'190–30'433	LFS
Slovenia	1999–2017	304	21'855–33'947	LFS
South Africa	2012–2019	228	11'965–12'201	QLFS
Spain	1999–2017	857	25'102–37'233	LFS
Sri Lanka	2012–2012	1	9'653–9'653	STEP
Sweden	1999–2017	1'312	34'468–47'892	LFS
Switzerland	1999–2017	397	42'028–62'927	LFS
Uganda	2009–2013	17	1'571–1'759	LSMS
Ukraine	2012–2012	1	9'956–9'956	STEP
United Kingdom	1999–2017	654	31'110–42'138	LFS
United States	2002–2016	372	46'828–55'265	CPS
Viet Nam	2012–2012	2	4'917–4'917	STEP
		18'168	1'248–99'477	

Note: Table A6 includes the underlying sources for the dataset used in Section 3.

Table A7: Work from home measures across detailed subgroups.

		Males				Females			
		HS Graduate		HS Dropout		HS Graduate		HS Dropout	
	Full Sample	Wage Employee	Self-Employed	Wage Employee	Self-Employed	Wage Employee	Self-Employed	Wage Employee	Self-Employed
One-Digit Occupation	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Managers	0.655	0.697	0.571	0.636	0.405	0.807	0.649	0.575	0.403
Professionals	0.622	0.628	0.619	0.266	0.575	0.640	0.589	0.442	0.273
Technicians and Associate Professionals	0.585	0.608	0.539	0.401	0.153	0.628	0.828	0.665	0.111
Clerical Support Workers	0.691	0.639	0.496	0.496	0.583	0.760	0.834	0.636	0.479
Services and Sales Workers	0.385	0.456	0.347	0.435	0.222	0.439	0.411	0.370	0.350
Skilled Agricultural, Forestry and Fishery Workers	0.227	0.391	0.261	0.100	0.094	0.411	0.627	0.339	0.298
Craft and Related Trades Workers	0.304	0.196	0.145	0.130	0.209	0.614	0.481	0.586	0.473
Plant and Machine Operators, and Assemblers	0.250	0.245	0.203	0.161	0.190	0.558	0.049	0.430	0.165
Elementary Occupations	0.379	0.262	0.102	0.191	0.260	0.589	0.351	0.507	0.451
Sample Average	0.450	0.495	0.368	0.261	0.206	0.620	0.483	0.476	0.367
Observations	17,598	3,599	1,299	1,923	1,422	3,918	1,277	1,659	2,501

Source: Source: Skills Toward Employability and Productivity (STEP) Survey. Note: Table A7 documents the share of workers who can work from home across the 72 possible combinations of 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 A8: Work from home employment and GDP per capita

	Share of employment that can Work from Home				
	Total employment	Urban employment	Urban Self-employed	Urban Low skilled	Urban female
	(1)	(2)	(3)	(4)	(5)
GDP per capita (ppp), log	0.055	0.046	0.051	0.007	0.047
	(0.007)	(0.005)	(0.006)	(0.006)	(0.005)
Constant	−0.079	0.026	−0.092	0.247	0.113
	(0.063)	(0.048)	(0.056)	(0.056)	(0.045)
Observations	57	57	57	57	57
R^2	0.559	0.613	0.589	0.024	0.641

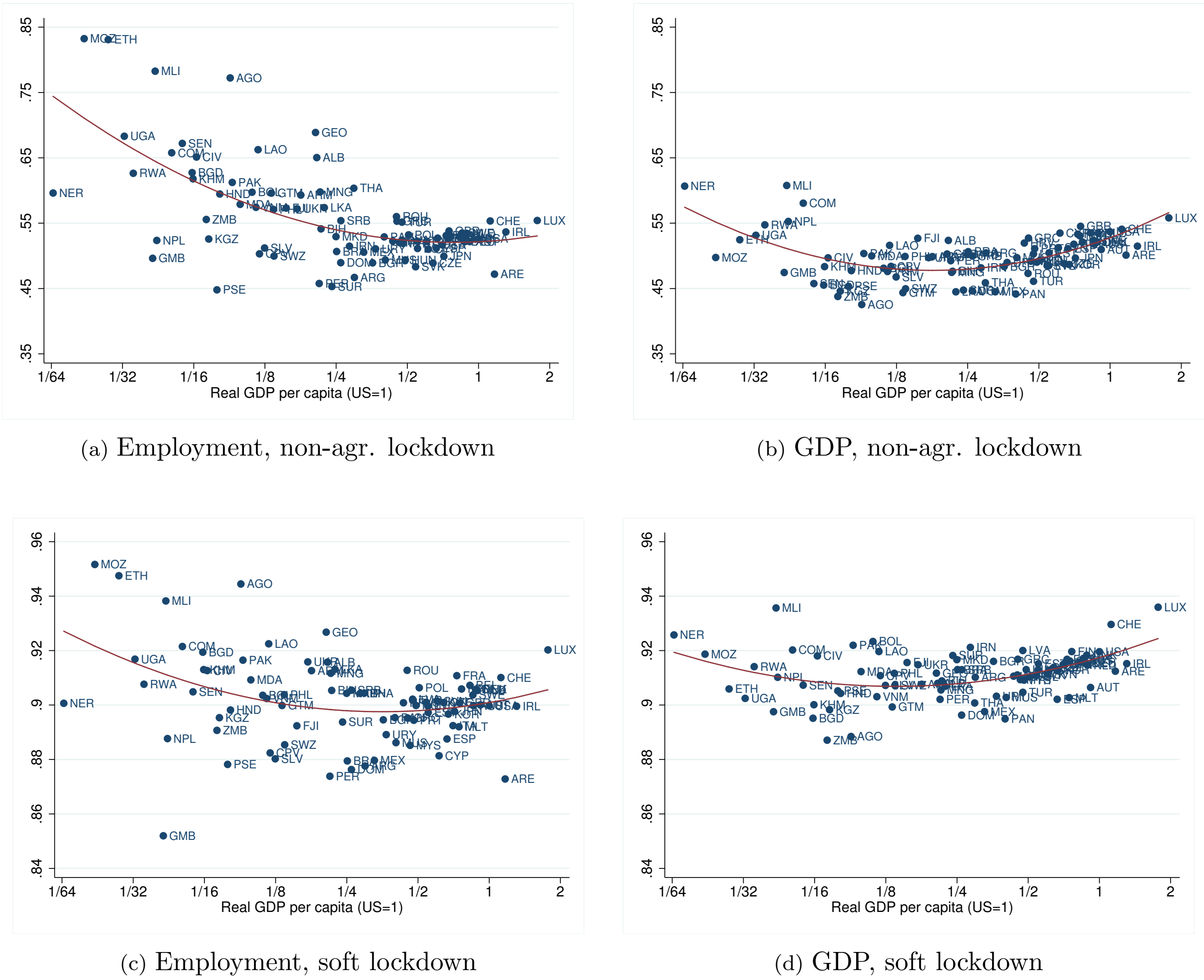
Note: Table A8 presents evidence from a country-level regression of log GDP per capita against different WFH measures. The analysis covers the 57 countries included in Table A6.

Table A9: Feasibility of working from home by occupation and industry

	STEP-Based Industry			
	Agriculture, Fishery, Mining	Manufacturing, Constr. & Transp.	Commerce	Other Services
One-Digit Occupation	(1)	(2)	(3)	(4)
Managers	0.539	0.584	0.641	0.708
Professionals	0.611	0.747	0.728	0.611
Technicians and Associate Professionals	0.489	0.588	0.664	0.583
Clerical Support Workers	0.646	0.617	0.655	0.732
Services and Sales Workers	0.522	0.344	0.358	0.436
Skilled Agricultural, Forestry and Fishery Workers	0.215	0.312	0.444	0.542
Craft and Related Trades Workers	0.105	0.314	0.260	0.315
Plant and Machine Operators, and Assemblers	0.272	0.284	0.250	0.234
Elementary Occupations	0.190	0.189	0.312	0.481
Industry-Average	0.266	0.366	0.395	0.536
Observations	929	3,195	4,048	8,127

Source: Skills Toward Employability and Productivity (STEP) Survey. Note: Table A9 documents the share of workers who can work from home by one-digit occupation and industry categories available in STEP data. Results include workers for whom industry information is available. Results are weighted using sample weights to represent the working-age population of 15-64 year olds in each STEP country.

Figure A1: Effective employment and GDP relative to trend under non-agricultural and soft lockdowns



(a) Employment, non-agr. lockdown

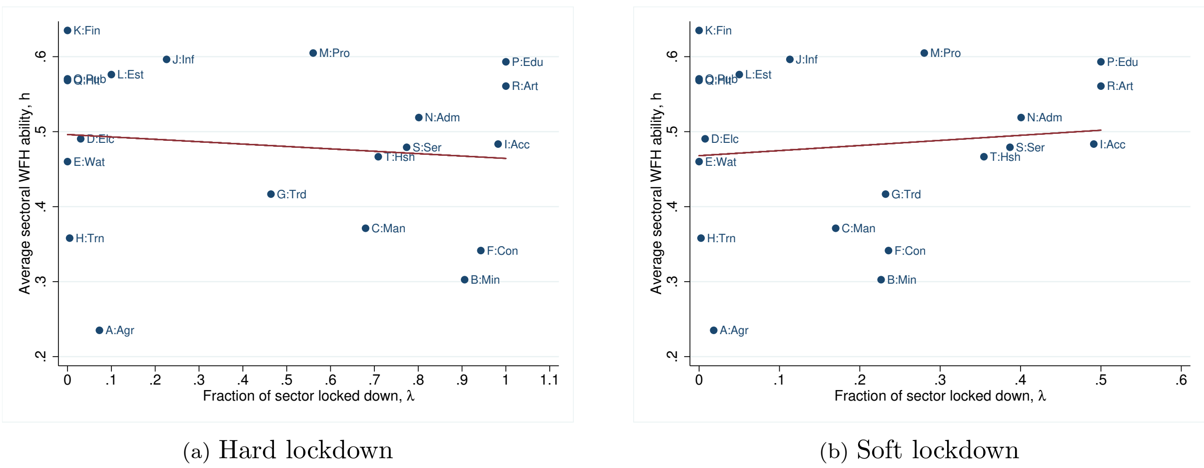
(b) GDP, non-agr. lockdown

(c) Employment, soft lockdown

(d) GDP, soft lockdown

Real GDP per capita of each country corresponds to the 2017 PPP-adjusted series from Feenstra et al. (2015), normalized to the U.S. The trend line is a quadratic fit of the logarithm of real GDP per capita.

Figure A2: Average sectoral WFH ability across countries and fraction of sector that shuts down

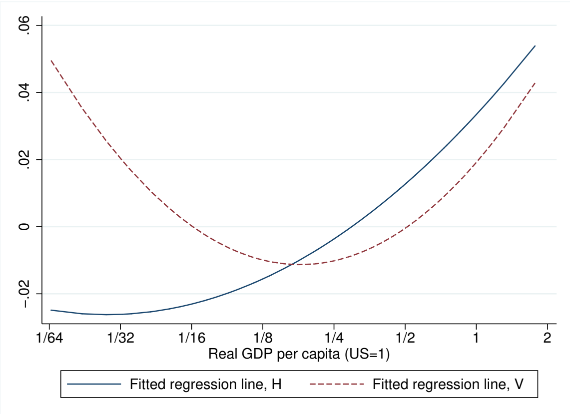


(a) Hard lockdown

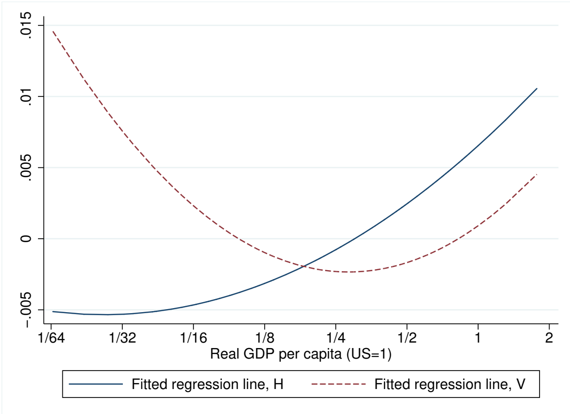
(b) Soft lockdown

Figure A2 presents estimated WFH ability for one-digit ISIC sectors, averaged across countries, along with the share of employment that can be carried out in a hard and soft lockdown in panels A and B, respectively. We present the line of best fit in both panels.

Figure A3: Fitted components H and V under the hard and soft lockdowns



(a) Hard lockdown



(b) Soft lockdown

In each scenario, the plots are the fitted lines $\hat{H}$ and $\hat{V}$ of the respective regressions $H = \beta_0 + \beta_1 \log GDP + \beta_2 (\log GDP)^2 + \varepsilon$ and $V = \gamma_0 + \gamma_1 \log GDP + \gamma_2 (\log GDP)^2 + \varepsilon$. In the hard lockdown scenario, the regression coefficients and t-statistics (in parenthesis) are $\hat{\beta}_1 = 0.033$ (9.13) and $\hat{\beta}_2 = 0.005$ (4.45), with $R^2 = 0.752$ for H, and $\hat{\gamma}_1 = 0.035$ (2.45) and $\hat{\gamma}_2 = 0.010$ (2.50), with $R^2 = 0.072$ for V. In the soft lockdown, we have $\hat{\beta}_1 = 0.007$ (9.20) and $\hat{\beta}_2 = 0.001$ (4.42), with $R^2 = 0.758$ for H, and $\hat{\gamma}_1 = 0.005$ (1.90) and $\hat{\gamma}_2 = 0.002$ (2.65), with $R^2 = 0.112$ for V.

A.2 Data sources

Our individual level dataset consolidates labor force surveys and the labor force section of household surveys for 57 countries. It contains information on individual characteristics, employment status, job type, occupation and sector of activity. Table A6 lists the data sources, the GDP per capita (ppp) that corresponds to the country year of the dataset taken from Zeileis (2019), as well as the sample size. Note that the sample size here corresponds to the number of working-age individuals (age 15-64) that work.

A.3 Model derivation

Here we derive the model that underpins equation (5) that used to calculate GDP relative to trend. Consider a closed economy where gross output in sector i is

$$g_i = z_i x_i^{\theta_i} \prod_{j=1}^{I} m_{ij}^{\gamma_{ij}},$$

with parameters $\theta_i \in [0,1]$ and $\gamma_{ij} \in [0,1]$ such that $\theta_i + \sum_{j=1}^{I} \gamma_{ij} = 1$. The sector's TFP is z_i and there are two types of production factors: x_i is a bundle of the sector's human and physical capital and m_{ij} is intermediate consumption of goods from sector j. Let p_i denote the price of output of sector i. Assuming perfect competition, profit maximization with respect to intermediate inputs implies $p_j m_{ij} = \gamma_{ij} g_{ij}$, $\forall i, j$. In particular, the sector's value added equals

$$V_i \equiv p_i g_i - \sum_{j=1}^{I} p_j m_{ij} = \theta_i p_i g_i.$$

The representative household chooses final consumption c_i to maximize utility

$$Y = \prod_{s=1}^{I} c_i^{\phi_i}$$

with parameters $\phi_i \in [0,1]$ such that $\sum_{i=1}^{I} \phi_i = 1$. The optimality condition is hence $p_i c_i = \phi_i Y$, $\forall i$. The product market clears according to $c_i + \sum_{j=1}^{I} m_{ji} = g_i$, $\forall i$.

Let Y denote real GDP and $P \equiv 1$ its normalized price so that $PY = Y = \sum_{i=1}^{I} p_i c_i$. In equilibrium, it can be shown that GDP is

$$Y \propto \prod_{i=1}^{I} \left(z_i x_i^{\theta_i} \right)^{d_i}$$

with parameter vector $d = \phi'(I - \Gamma)^{-1}$ where I is the identity matrix and Γ is the matrix with elements γ_{ij}. In particular, d_i equals the Domar weight of sector i, $d_i = \frac{p_i y_i}{Y}$. If z_i is constant and the only exogenous shock occurs through the supply of x_i, then $Y \propto \prod_{i=1}^{I} x_i^{\nu_i}$ where $\nu_i = \theta_i d_i = \frac{V_i}{Y}$ equals the (constant) aggregate value added share of sector i in the economy. GDP relative to trend is then $y \equiv \frac{\tilde{Y}}{Y} = \prod_{i=1}^{I} \left(\frac{\tilde{x}_i}{x_i} \right)^{v_i}$ where $\tilde{x}_i / x_i$ denotes the relative utilization of factor x_i following the shock. Our final assumption is that capital and labor (l) enter homothetically into x and that they change in equal proportion following the shock, resulting in

$$y \equiv \frac{\tilde{Y}}{Y} = \prod_{i=1}^{I} \left(\frac{\tilde{l}_i}{l_i} \right)^{v_i}.$$

Economies can differ in their underlying parameters, which implies that v_i is country-specific.

A.4 Lockdown scenarios

Table A10 summarizes the percent of sectoral workplace employment that is shut down under the various lockdown senarios used in section 4. The complete lockdown signifies that all sectors are shut down. The non-agricultural lockdown signifies that all sectors except agriculture are shut down, i.e., $\lambda = 0$ for agriculture and $\lambda = 1$ in all remaining sectors.

Table A10: Lockdown scenarios, percent of sectoral workplace employment that is shut down

	Complete	Non-agr.	Hard	Soft
Agriculture / forestry / fishing (A)	100	0	7	2
Mining and quarrying (B)	100	100	91	23
Manufacturing (C)	100	100	68	17
Electricity / gas / steam / air cond. (D)	100	100	3	1
Water supply / sewerage (E)	100	100	0	0
Construction (F)	100	100	94	24
Wholesale and retail trade (G)	100	100	46	23
Transportation and storage (H)	100	100	0	0
Accommodation and food service (I)	100	100	98	49
Information and communication (J)	100	100	23	11
Finance and insurance (K)	100	100	0	0
Real estate (L)	100	100	10	5
Professional / scientific / technical serv. (M)	100	100	56	28
Administrative and support services (N)	100	100	80	40
Public administration and defence (O)	100	100	0	0
Education (P)	100	100	100	50
Health and social work (Q)	100	100	0	0
Arts / entertainment / recreation (R)	100	100	100	50
Other service activities (S)	100	100	77	39
Private households with empl. persons (T)	100	100	71	35

Note: Table A10 presents the share of sector-level employment which is shutdown under four lockdown scenarios. See Section 4 for details.

The hard lockdown is based on Fana et al. (2020) who encode the March 2020 legislative confinement measures in Germany, Italy and Spain. In particular, they report for each country the degree to which two-digit ISIC sectors are considered essential and therefore the degree to which they are allowed to function normally. Their final index is an average across the three countries, justified by the fact that there is relatively little discrepancy between them. To aggregate up to one-digit sectors, we use employment weights: $\lambda_i = 1 - \sum_{j \in i} \mu_j e_j$, where $e_j \in [0, 1]$ is the essential index and μ_j is the employment share of the two-digit sectors j belonging to one-digit sector i.[28]

We perform two manual changes. Fana et al. (2020) document that the sector *Education* (ISIC code P) is entirely essential in Germany and Italy, while non-essential in Spain, implying $\lambda = 0.33$. Instead, we shut it down completely, $\lambda = 1$. Our choice is guided by the fact that

[28]The employment shares are averaged across all available countries using the ILO data at the two-digit ISCO level.

both Germany and Italy closed down all educational establishment in March 2020. Second, according to Fana et al. (2020), the sector *Real estate activities* (ISIC code L) is completely non-essential, implying $\lambda = 1$. Instead, we assign it the value $\lambda = 0.1$. We conjecture that restrictions to real estate employment activities such as brokerage have a minimal impact on bulk of the sector's value added, which consists mainly of imputed own-occupied housing as well as established rental arrangements.

Finally, in the soft lockdown scenario, we reduce the value of λ from the hard lockdown by a fraction, namely by 75% for agriculture and industry (ISIC codes A-F) and 50% for services (ISIC codes G-T). This is guided by the notion that service sectors require more interaction with customers and are therefore more likely to suffer restrictions.

Figure A2 plots the average WFH ability of sectors across countries relative to the degree to which sectors are shut down, λ. Neither in the hard nor in soft lockdown there exists a clear relationship between the two variables, meaning that on average the propensity to exercise WFH does not correlate with how essential a sector is.

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