Working from Home: Implications for Developing Countries*

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1 Introduction

In the fight to contain the spread of Covid-19, 70 countries across the world have implemented social distancing policies.[1] These policies have severe economic effects because they limit the ability to work for a large number of workers. However, some workers may be able to continue working if they can work from home. Measuring the ability of a country's employment to work from home is, therefore, crucial to understanding the effects of social distancing policies on incomes and welfare. Conversely, an assessment of how much work can be done from home is a key input for the design of social distancing rules and social protection responses.

The ability to work from home (WFH) foremost depends on the nature of a job. Essentially, if a job requires the use of machinery (or other infrastructure) or physical interaction with colleagues or customers, it can not be done from home. The prevalence of such jobs differs across countries. In particular, it differs systematically with development, given the well-known changes in the sectoral and occupational structure of economies with development (Kuznets, 1973; Gollin, 2008; Herrendorf et al., 2014; Duernecker and Herrendorf, 2016).

The ability to work from home also differs significantly across workers in an economy. Understanding these differences is essential to anticipate the unequal effects of social distancing policies and design appropriate policies to alleviate the effects on those worst affected.

In this chapter, we lay out evidence on the various factors which determine the feasibility of working from home, and analyze their implications for the aggregate ability to WFH as well as for distributional aspects.[2] We first focus on differences across countries, with a particular focus on differences across levels of development.[3] For this analysis, we use the occupation-level data on WFH ability measured by Dingel and Neiman (2020). Large differences in the ability

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[1] Retrieved from `https://en.wikipedia.org/wiki/Template:COVID-19_pandemic_lockdowns` on May 27, 2020.

[2] The evidence presented here closely draws on Saltiel (2020) and Gottlieb et al. (2020).

[3] Recent months have seen work documenting potential and actual WFH in a variety of individual countries; see e.g. Barrot et al. (2020), Boeri et al. (2020), del Rio-Chanona et al. (2020), Fadinger et al. (2020), Hensvik et al. (2020), Koren and Pető (2020) and Mongey and Weinberg (2020). Dingel and Neiman (2020) compute WFH potential for a broad cross-section of countries using occupation-level data and Hatayama et al. (2020) develop a comparable WFH measure across 53 countries. Adams-Prassl et al. (2020) study differences in the ability to work from home within occupations.

to WFH across occupations imply that the aggregate ability to WFH in a country is closely determined by the share of employment in certain occupations, in particular in agriculture, and by the share of self-employment. Using a dataset containing information on millions of workers in 57 countries across the entire spectrum of the distribution of country income per capita, we calculate the aggregate WFH ability for these countries, as well as figures for selected subgroups.

This analysis yields two main findings. First, the ability to WFH in urban areas – where social distancing is particularly important – is significantly lower in developing countries. This is mainly due to the concentration of employment in elementary, services, and sales occupations in particular among the large group of the self-employed. For the wage employed, differences with income per capita are less pronounced. This indicates that policies need to pay particular attention to the self-employed. Second, the effect of social distancing policies on aggregate employment (including rural areas) depends crucially on how their design affects self-employed farmers. If social distancing policies still allow them to work, their overall effect on the ability to work is not systematically larger in developing countries.

We then proceed to an in-depth analysis of the ability to WFH at the individual level, using data from 10 countries at very different levels of development. This dataset allows us to single out worker types that are less able to work from home and more vulnerable to social distancing policies. We find particularly low ability to WFH for workers in services and sales occupations, in occupations that are most prevalent in manufacturing, and for the self-employed. Also, we find that workers with low levels of education or assets are less likely to be able to WFH. Women, in contrast, are more likely to be able to WFH. These patterns are surprisingly stable across countries. Most groups with a lower ability to WFH are also poor. Hence, it is the urban poor who are most likely to experience large income losses from social distancing policies.

Our findings provide guidance as to the likely effects of strict social distancing policies on aggregate outcomes and the livelihoods of specific groups. They can help to anticipate how deep a recession generated by social distancing policies will be, and identify groups most in need of support due to income loss.

2 Cross-Country Evidence

We begin by providing country-level evidence on the ability to work from home for a comprehensive cross-section of countries at different levels of economic development. The income gradient of the ability to WFH helps us understand how countries at various stages of development may be affected by social distancing policies. To do so, we use individual-level information on workers across many countries and information on the ability to work from home across occupations.

Several recent papers have developed measures of the ability to work from home across occupations using data from a wide range of countries (see footnote 3). We focus on the measure by Dingel and Neiman (2020), who were the first to develop a measure of how much work could potentially be done from home. They use a task-exclusion approach and data on occupation characteristics from the US Occupational Information Network (O*NET). In particular, they define whether an occupation can be carried out at home based on information on 38 task attributes of an occupation. Their approach consists in excluding work from home when certain conditions are true. For example, an occupation is classified as not permitting work from home if workers lift heavy loads, use or repair particular types of machinery, or do not use e-mail at work.[4]

[4] This approach contrasts with simply measuring how much work is already done from home, which likely is lower than the potential to WFH. Other researchers have developed similar measures for other data sources and countries, adjusting the exact criteria used based on data availability. Our analysis in Section 3 follows a similar approach.

Dingel and Neiman (2020) apply this method to O*NET data on occupation characteristics and provide measures of the share of employment that can be done from home for many occupations. We use this information to compute for a broad occupation category (ISCO-08 1-digit) the fraction of detailed occupations within a broad occupation group, which we report in Table 1, and compare with the evidence presented in Saltiel (2020).

Table 1: Percent of jobs that can be done from home by ISCO-1 occupation group

	Occupation, ISCO 1 digit	WFH (in %)	
		Dingel and Neiman (2020)	Saltiel (2020)
1	Managers	76.8	34.0
2	Professionals	70.6	34.4
3	Technicians and Associate Professionals	39.6	27.4
4	Clerical Support Workers	49.6	41.8
5	Services and Sales Workers	20.7	6.4
6	Skilled Agricultural, Forestry and Fishery Workers	8.3	0.1
7	Craft and Related Trades Workers	3.9	3.3
8	Plant and Machine Operators and Assemblers	7.4	0.5
9	Elementary Occupations	9.6	2.3

Note: The first column uses the classification based on ONET data provided by Dingel and Neiman (2020) and use a cross-walk to the ISCO-1 classification. The second column reports the ability to work from home that we measure in Section 3.

It is very clear from Table 1 that the ability to work from home differs very strongly across broad occupation groups. While most jobs in managerial and professional occupations can be done at home, this is the case for only a small fraction of jobs in elementary or manufacturing occupations (like plant and machine operation). The ability for services and sales workers to work from home is also low. This broad difference in WFH ability between professional, services, and manufacturing-related occupations is crucial, since the share of employment in these occupations differs a lot across countries. Saltiel (2020)'s definition yields similar patterns in WFH feasibility across occupations. As discussed below, his analysis relies on information task content in developing countries, thus yielding lower WFH shares within occupations.

We combine the measure from Table 1 with data on employment by occupation across countries. We take this data from our micro-dataset we built merging household surveys and labor force surveys from 57 countries, covering 612 country-years.[5] It contains individual-level data on 18 million individuals that work and covers many countries at different stages of development ranging from Ethiopia to Luxembourg. While alternative data sources such as the ILO also offer a wide cross-country coverage, our micro-dataset allows us to compute population and employment shares for many subgroups of the working population.

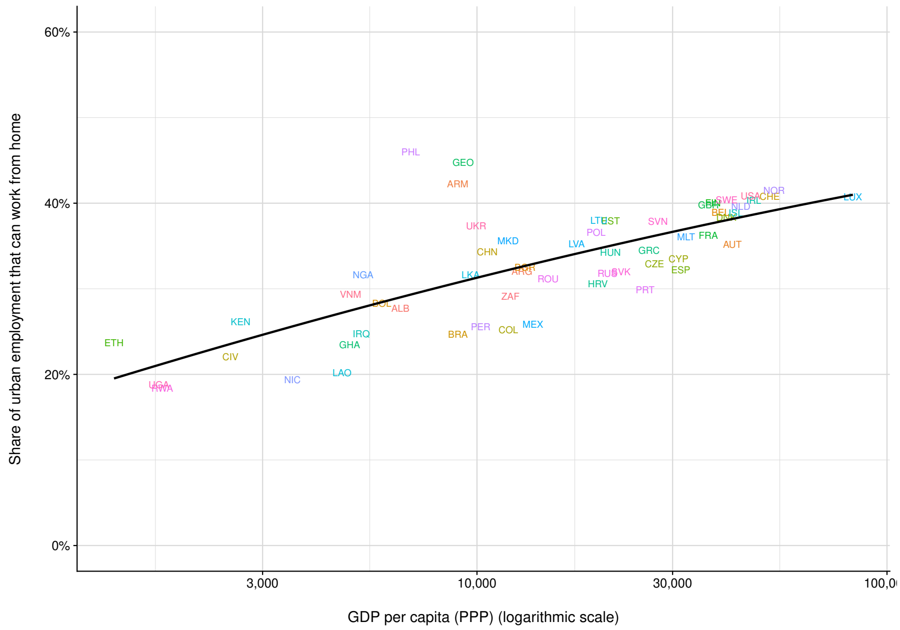
We first examine the ability to WFH for workers in urban areas, where social distancing policies are particularly important. Our data reveal that the distribution of employment over broad occupations differs very strongly with country income, even in urban areas. High-income countries have more than half of their urban employment in the first four broad occupations (managerial and professional occupations). In contrast, these occupations account for barely a fifth of urban employment in the poorest countries. Low-income countries instead have large shares of urban employment in elementary occupations as well as services and sales (each around 30%). In high-income countries, these occupations account for only 10 and 15 percent of urban employment, respectively.

Using information on the share of employment in each occupation, we compute the total WFH ability for each country. Figure 1 shows WFH ability by country for urban areas. It is clear that, as a consequence of the large differences in employment composition, the ability to WFH for urban workers varies strongly with income per capita. For high-income countries, we

[5] A full overview of the data sources is provided in Table 3

find that just under 40% of work can be done from home – in line with the numbers reported by DN. For low-income countries, this share is cut almost by half. These numbers are fairly homogeneous across countries in a country income group, with just very few exceptions.

Figure 1: Percent of urban workers who can work from home by income per capita



Note: Figure 1 shows the share of the urban employed population with an occupation that can be executed remotely by country year. The data sources for the occupation employment shares are displayed in Table 3. The GDP data is taken from Feenstra et al. (2015); Zeileis (2019), and the share of WFH jobs by occupation is from Table 1.

Table 2 shows WFH ability by country income group, both for all urban workers and for some subgroups of workers. This table reveals another striking feature: the ability to WFH does not vary strongly with country income per capita for wage employees, but it differs very strongly for the self-employed. This occurs because the self-employed, in particular in poor countries, are concentrated in elementary occupations (almost 40%) and services and sales occupations (almost 45%), where WFH is particularly difficult. In contrast, in high-income countries, the occupation distribution does not vary much between wage employees and the self-employed. Hence, it is the occupational employment distribution of the self-employed, combined with the very high rates of self-employment in poor countries (Gollin, 2008), that explains the lower ability to WFH in poor countries.

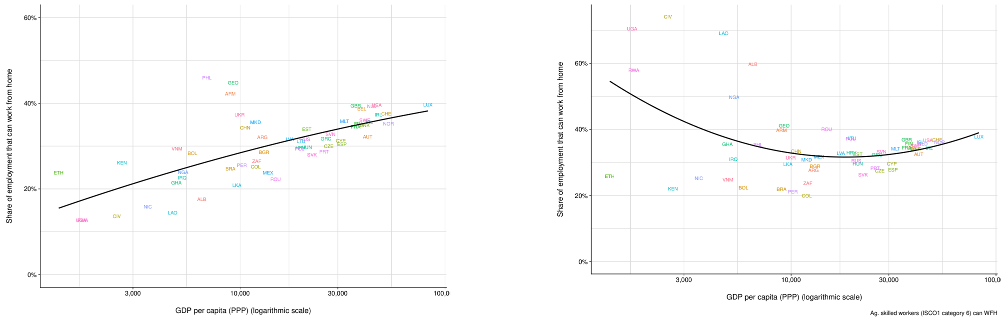
Table 2: Percent of workers who can work from home by country income level

	Low	Lower-middle	Upper-middle	High
Urban	22.1	29.6	31.2	37.1
Urban, wage employed	28.0	32.9	31.7	36.7
Urban, self-employed	15.5	23.8	28.8	40.4
Urban and rural	14.7	24.8	28.8	34.7
Urban and rural, WFH for farmers =1	64.3	42.9	34.2	37.5

Note: The numbers represent averages across country-years' WFH employment shares within each income group as defined by the World Bank classification in 2018.

Finally, we assess the ability to WFH at the level of the entire country. Since high-income countries are highly urbanized, it will not differ significantly from that in urban areas. However, developing countries have large shares of employment in rural areas, and particularly in

Figure 2: Percent of a country's workers who can work from home by income per capita



(a) Baseline WFH scores

(b) WFH score of 1 for agricultural workers.

Note: Data sources as in Figure 1. Panel (a) is analogous to that figure, using data for the country. Panel (b) is similar, except for the assumption that the ability to WFH is 1 for the occupation "Skilled Agricultural, Forestry and Fishery Workers".

agriculture, with agricultural employment shares of over 50% in some countries. Hence, their ability to WFH can differ significantly between rural and urban areas.

The large agricultural employment shares in developing countries imply that the ability to WFH in agriculture is the primary determinant of their aggregate ability to WFH. Based on O*NET data, only 8.3% of jobs in agriculture can be done from home. This assessment is based on the way agricultural work is done in the United States, in terms of both tasks on the job and the size of farms. Clearly, employees on large farms are unable to work from home. However, in most low-income countries, agricultural employment is dominated by small-scale subsistence agriculture, and wage employment plays a small role. A significant portion of farm output is consumed within the farming household and not sold to the market (Eastwood et al., 2010; Adamopoulos and Restuccia, 2014; Gollin and Rogerson, 2014; Alvarez-Cuadrado et al., 2020). In such a situation, it may be feasible for a large fraction of agricultural work to be done from home by self-employed farmers without employees on their plots in the vicinity of their homes. Middle-income countries fall in between since their agricultural employment features a combination of subsistence farms and larger farms with employees.

Figure 2 shows the aggregate WFH ability across countries for the two extreme scenarios: one where WFH ability in agriculture is only 8.3% on the left, and one where all the self-employed in agriculture can work from home on the right. The true WFH ability in agriculture will lie in between and depends on the marketization of agriculture and, in particular, the extent to which small-scale farmers purchase inputs and sell output in markets.

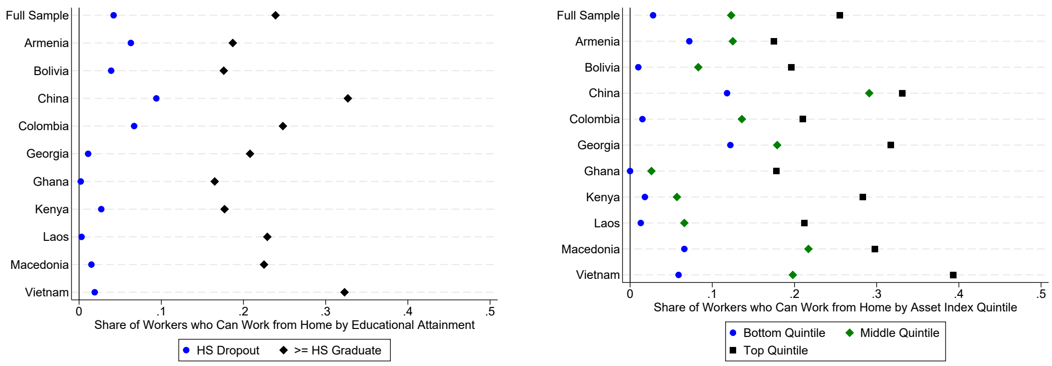
Results are striking and show that farmers' ability to WFH is crucial. If farmers' ability to WFH is low, the aggregate ability to WFH in low-income countries hovers around 20%, similar to that in urban areas (and half that in high-income countries). But if farmers can work from home, it rises to 30 to 70%, and exceeds that in high-income countries.

These findings illustrate that the rigidity of social distancing rules applied to farmers will be essential in determining the potential to WFH in developing countries. It seems plausible that self-employed farm work is possible while preserving adequate social distancing. Permitting it will then have a large effect in preserving labor input in developing countries, and limiting adverse effects of social distancing on labor supply and incomes.

3 Within-Country Differences

The evidence discussed so far considers the feasibility of WFH at the occupation-level, yet sizable heterogeneity may exist in workers' abilities to work from home *within* occupations. To this end,

Figure 3: Characteristics of Workers who Can Work from Home by STEP Country



(a) WFH By HS Dropout Status

(b) WFH By Asset Index Quintile

Source: Skills Toward Employability and Productivity (STEP) Survey.
Note: Figure 3 presents the share of jobs which can be done from home in the full sample and across STEP countries by workers' high school dropout status (Panel A) and asset index quintile (Panel B).

we take advantage of worker-level data on task content from the Skills Toward Employability and Productivity (STEP) survey, which covers workers in urban areas in ten countries, including Armenia, Bolivia, China (Yunnan Province), Colombia, Georgia, Ghana, Kenya, Laos, Macedonia and Vietnam. STEP includes extensive information on workers' employment outcomes, covering their occupation and self-employment status, as well as on observed characteristics, including educational attainment, gender and a household-level asset index. As a result, we can identify the types of workers who are more likely to be able to work from home during lockdowns.

To measure workers' ability to work from home, we leverage information on the tasks they perform at work. In particular, we follow Dingel and Neiman (2020) and rule 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. Across the STEP sample, 40% of workers lift heavy items at work and 27% report having frequent interactions with their customers.[6] Combining the various task exclusions outlined above indicates that just 13% of workers in STEP countries can work from home according to this definition. In line with the results presented in Section 2, the prevalence of WFH is positively correlated with countries' levels of economic development.

Moreover, analyzing the characteristics of workers who may carry out their work from home can help inform the likely impacts of lockdowns on livelihoods and inequality. To this end, we present evidence on the WFH measure by workers' educational attainment in the first panel of Figure 3. We find that while 24% of workers who have at least completed a high school degree may work from home, this is the case for just 4.2% of their counterparts who did not finish high school. These differences are present across all countries in the STEP sample, and largest in Vietnam, reaching close to 30 percentage points. In the second panel, we further show sizable disparities in the ability to WFH across households' ranking in the within-country asset distribution: on average, just 2.8% of workers in the bottom asset quintile can work from home, far behind than their peers in the top quintile at 25.5%. This result highlights the extent to which Covid-19 may exacerbate existing inequalities, as almost no workers who are unable to work from home may successfully self-insure against the negative shock.

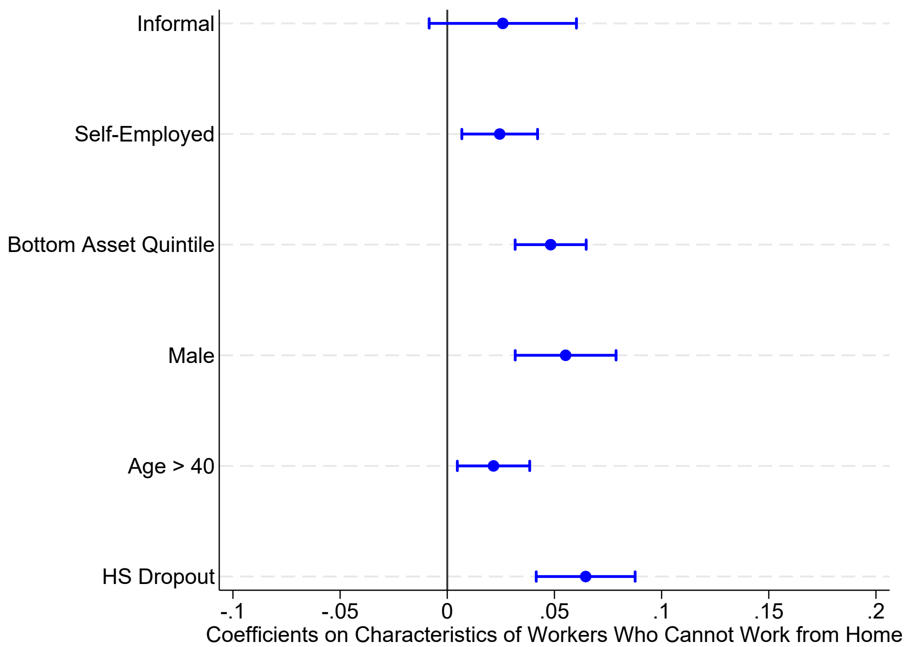
[6]We weigh observations by each country's population of 15-64 year olds. STEP sample averages thus give greater weight to countries with larger populations.

We have so far shown that high-paying occupations and more educated workers have a higher likelihood of working from home. To discern the relative importance of occupations and workers' observed characteristics, we estimate the following regression using STEP data:

$$NWFH_{ijc} = \beta_0 + \beta_1 \boldsymbol{X_i} + \gamma_j + \lambda_c + \varepsilon_{ijc} \tag{1}$$

where $NWFH_{ijc}$ is a binary variable which equals 1 if worker i in occupation j in country x cannot work from home, $\boldsymbol{X_i}$ includes workers' observed characteristics, γ_j is a three-digit occupation fixed effect and λ_c denotes country fixed-effects. We present the results in Figure 4. We find that high school dropouts, those in less wealthy households, males, older workers and self-employed workers are less likely to be able to work from home even within narrowly defined occupational groups. For instance, high school graduates are 6.5 percentage points more likely to be able to work from home than their counterparts who did not complete high school within three-digit occupations. Altogether, these results indicate that more vulnerable workers are far less likely to continue working from home. As such, government interventions will play a critical role in relieving workers who cannot pursue their income-generating activities and these policies should account for workers' vulnerabilities even within-narrowly defined occupations (Gentilini and Almenfi, 2020).

Figure 4: Within-Occupation Worker Characteristics Associated with Not Working from Home



Source: Skills Toward Employability and Productivity (STEP) Survey.

Note: Figure 4 presents the estimated coefficients from equation (1) for the full STEP sample, including country fixed effects and three-digit occupation fixed effects. Results are weighted 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.

4 Conclusion

The impact of social distancing and lockdown policies on livelihoods largely depend on the ability of workers to pursue their income-generating activities from home. In the developing world, in particular in urban areas, workers are much less likely to be able to work from home than in high-income countries, because a large share of workers are self-employed and pursue jobs that require infrastructure and proximity with customers. At the national level, this conclusion hinges on the ability of farmers to work from home. If they can work while respecting social distancing guidelines, the overall ability to work from home in low-income countries is similar to that in high-income countries.

At the individual level, we show that low-skilled, old and self-employed workers are less likely to be able to work from home. At the same time, they are more likely to be asset poor, and therefore unable to self-insure. To avoid increases in poverty rates in the developing world, government interventions that target these groups should be set high on the policy agenda.

Research on social distancing, work from home, and their effects is proceeding rapidly. As evidence accumulates, future work should aim to validate the various WFH measures in the literature. In particular, it would be useful to establish to what extent the *inability* to work from home leads to income losses, and how individual attributes, economic conditions, institutions and policies affect this.

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Appendix

Our individual level dataset consolidates labor force surveys and the labor force section of household surveys for many countries. This dataset harmonizes information on individual characteristics and labor supply. It contains information on employment status, job type, occupation and sector of activity. Table 3 lists all data sources used to construct the dataset.

Table 3: 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	23	4'845–9'918	LSMS
Argentina	2004–2006	127	12'074–13'770	LFS
Armenia	2013–2013	1	8'979–8'979	STEP
Austria	1999–2017	1'034	34'938–51'524	LFS
Belgium	1999–2017	474	32'357–46'522	LFS
Bolivia	2012–2012	2	5'860–5'860	STEP
Brazil	2002–2006	723	8'358–9'515	LFS
Bulgaria	1995–2017	177	6'390–20'027	LSMS, LFS
China	2012–2012	1	10'596–10'596	STEP
Colombia	2012–2012	2	11'934–11'934	STEP
Cote d'Ivoire	1985–1988	13	2'429–2'734	LSMS
Croatia	2002–2017	155	13'750–24'368	LFS
Cyprus	1999–2017	207	25'255–36'137	LFS
Czech Republic	2002–2017	663	21'374–36'061	LFS
Denmark	1999–2017	511	33'525–49'607	LFS
Estonia	1999–2017	118	10'772–31'013	LFS
Ethiopia	2013–2014	46	1'248–1'357	LFS, UES
Finland	1999–2017	207	31'433–42'902	LFS
France	2003–2017	812	31'567–40'975	LFS
Georgia	2013–2013	1	9'254–9'254	STEP
Ghana	2013–2015	6	4'875–4'910	STEP, LFS
Greece	1999–2017	1'143	22'683–31'340	LFS
Hungary	2001–2017	1'179	16'448–27'531	LFS
Iceland	1999–2017	54	37'732–51'316	LFS
Iraq	2006–2006	27	5'223–5'223	LSMS
Ireland	1999–2017	1'071	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	2001–2017	154	10'921–26'643	LFS
Lithuania	1999–2017	277	10'373–30'936	LFS
Luxembourg	1999–2017	168	64'436–99'477	LFS
Macedonia, The Former Yugoslav Republic of	2013–2013	2	11'910–11'910	STEP
Malta	2009–2017	76	26'792–41'847	LFS
Mexico	2005–2005	163	13'691–13'691	LFS
Netherlands	1999–2017	834	37'786–50'024	LFS
Nicaragua	2005–2005	12	3'548–3'548	LSMS
Nigeria	2010–2018	18	4'971–5'641	LSMS
Norway	2005–2017	111	49'908–63'768	LFS
Peru	2009–2014	115	8'515–11'086	LFS
Philippines	2015–2015	1	6'896–6'896	STEP
Poland	2006–2017	1'155	16'416–28'420	LFS
Portugal	1999–2017	771	22'413–28'567	LFS
Romania	2009–2017	694	16'752–25'262	LFS
Russian Federation	2004–2015	77	12'554–25'777	RLMS-HSE
Rwanda	2013–2016	49	1'551–1'872	LFS
Slovakia	2007–2017	354	22'724–30'433	LFS
Slovenia	2005–2017	297	26'506–33'947	LFS
South Africa	2012–2019	243	11'965–12'201	QLFS
Spain	1999–2017	920	25'102–37'233	LFS
Sri Lanka	2012–2012	1	9'653–9'653	STEP
Sweden	1999–2017	1'441	34'468–47'892	LFS
Switzerland	2010–2017	232	54'028–62'927	LFS
Uganda	2009–2013	21	1'571–1'759	LSMS
Ukraine	2012–2012	1	9'956–9'956	STEP
United Kingdom	1999–2017	702	31'110–42'138	LFS
United States	1998–2004	220	43'625–49'138	CEPR
Viet Nam	2012–2012	2	4'917–4'917	STEP
		17'892	1'248–99'477	