Emerging Economies and COVID-19
Shutting Down in a World of Informal and Tiny Firms*

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Abstract

Employment losses in 2020 were larger in Latin America than any other region. We show that the prevalence of informality, micro-entrepreneurship and jobs-not-fit for remote work in non-essential-sectors accounts for this performance in simulations and ex-post outcomes. Considering lockdowns and demand shocks, amplified by IO-linkages and a Keynesian-multiplier, the risk of job losses is five times as large in a typical Latin American economy than in a counterfactual US. Our framework accounts for over 70% of the second-quarter observed cross-sector variation in work hours. Early blanket-lockdowns, differentially affecting informality, as those implemented in part of Latin America, outweigh other factors.

Keywords: COVID-19, emerging economies, informality, firm-size distribution, Latin America.
JEL codes: F; O47; O20; O17

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1 Introduction

Latin America, together with South Asia, experienced the greatest declines in labor hours in 2020 due to COVID-19 (ILO, 2021). Informality and employment in micro-enterprises are prevalent in these emerging economies (EMEs), accounting for over 50% of the labor force. Workers in the informal sector lack employment protection and are frequently in hand-to-mouth activities, while very small firms lack access to financing to maintain employment relationships in times of low activity. These characteristics, together with the lesser degree to which jobs in EMEs can be conducted remotely, render workers in EMEs highly vulnerable to lockdown policies and sudden reductions in demand. At the same time, informal activities are likely to recover more easily from these shocks because they require little organizational capabilities compared to larger firms and incur no regulation-related hiring and firing costs.

This paper assesses the extent to which these distinctive characteristics of EMEs' labor markets made employment and income more vulnerable at the onset of the COVID-19 crisis and implied a differential path of recovery, relative to developed economies. To do so, we develop a framework where vulnerability to shocks associated with the pandemic depends on the distribution of employment across formality status, firm size categories, occupations, and sectors with varying degrees of exposure to demand reductions and lockdown policies.

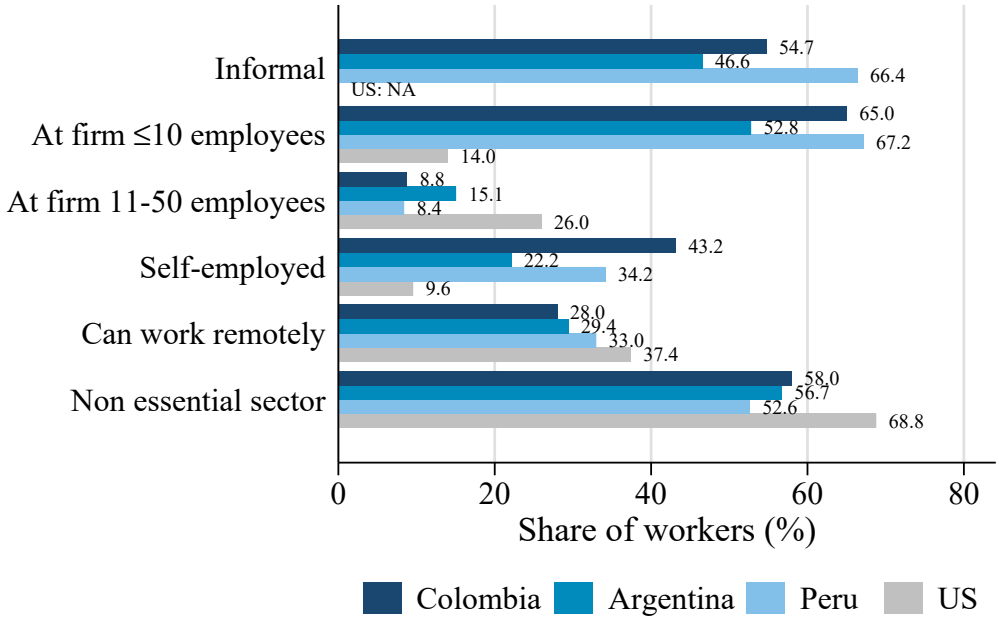
The extent to which employment is vulnerable to the crisis is given by the joint probability that the job is subject to one or several COVID-associated shocks and not protected by one or more of several attenuation factors. We consider three such shocks to employment in a given sector: (1) a direct supply shock, emerging from lockdown policies, affecting sectors classified as non-essential; (2) a demand shock driven by fear of infection, mostly affecting goods and services that require face-to-face interaction with customers; and (3) indirect supply and demand shocks, accounting for supply and demand shocks in downstream and upstream sectors. On the other hand, three attributes of workers and employment can attenuate the effects of COVID: (1) employment protection legislation that covers formal workers against discharge under certain circumstances; (2) the employer's ability to access funds to avoid discharging workers when faced with a sudden extreme revenue contraction, more likely in larger firms; and (3) the ability of the worker to work remotely. Aggregate job and income vulnerability are exacerbated by a Keynesian aggregate-demand multiplier.

We apply our framework to Argentina, Colombia and Peru, representative of Latin American countries (LAC) and other EMEs in that they have predominantly urban labor markets characterized by high informality and the prevalence of small firms.[1] These are also countries where predominant occupations are less fit for remote work than in a typical advanced economy. At least half of urban workers in Latin America hold informal jobs and an even higher fraction work in tiny firms (Figure 1).[2] In contrast, in the United States in 2019, only 14% of workers worked at firms

[1] LAC high urbanization rate was 80.9% in 2019 (United Nations).

[2] Eslava et al (2021) report similar characteristics for a wider sample of LAC countries.

Figure 1: Employment characteristics, urban areas of Argentina, Colombia, Peru and the United States



Note: Formality status is defined by the payment of mandatory pension contributions (Colombia, Argentina) an official indicator for informal employment (Peru). For the United States, self-employment encompasses those employed in their own business (incorporated and not incorporat ed), professional practice, and farming.
Source: Authors' calculations, based on Household Surveys from Argentina, Colombia and Peru (EPH, 2019; GEIH, 2019; ENAHO, 2019), the US Census's Business Dynamics Statistics (BDS, 2014), and the American Community Survey (ACS, 2017).

with 10 or fewer workers, around 10% were self-employed, and informality is so unimportant that it is not measured systematically. Figure 1 also shows that LAC countries tend to have less concentration on occupations fit for remote work than the United States (see section 2.2. for measurement details).

Understanding the impact of mobility restrictions remains crucial, at a time when the emergence of new COVID-19 variants prompts debate around the possibility of new closures. Much of what is known about these impacts comes from evidence for developed economies, leaving open the question regarding the effects under different economic structures. Argentina, Colombia and Peru adopted long-lasting blanket lockdowns that preceded initial waves of contagion, offering a good setting to study these issues. Despite the strict restrictions, these countries rank among the top 20 in

the world in cumulative COVID-19 deaths per capita, above the US. The tension between harsh mobility restrictions and the structure of the economy is arguably partially responsible for this negative outcome.

Stay at-home orders in these three economies were imposed in mid-March 2020, when only a handful of cases had been confirmed in each of them (Appendix Figure A1). Strict lockdown orders, more stringent than those adopted in most developed economies, lasted longer as well, for at least six months in Colombia and further in Argentina and Peru (see Figures A2-A5 in the Appendix). All outdoor and indoor activities were banned, except the purchase, production and distribution of essentials. Production restrictions were eased progressively starting in June 2020, while other mobility restrictions remained, including in-person education, recreational activities and inter-city transportation. The sharp contraction in mobility (see Appendix) shows that there was high compliance with lockdowns, particularly during the first few months.

We first assess how job and income vulnerability to the crisis differ in magnitude between a typical LAC economy modeled after Argentina, Colombia and Peru, and an advanced economy modeled after the US. Our baseline scenario imposes a lockdown on all non-essential economic activities. The demand contraction in each sector matches that observed in an economy where lockdowns were not imposed, adjusted to the Latin American economic structure. The indirect effect of shocks in downstream and upstream sectors is calculated relying on the IO matrix.

We find that, compared to baseline data for 2019, almost 50% of jobs and 30% of aggregate value added are at risk under scenarios were non-essential-sector jobs that are informal or in micro-enterprises are hit. Jobs and income at risk decrease to 9.8% and 7.2% respectively if the distribution of employment in the United States is imposed on the Colombian data. Lockdowns imposed on all non-essential activities account for 74%-80% of the jobs at risk in the baseline simulation; sector-specific demand reductions explain less than 10%. The informal sector has low entry costs; thus, as the economy recovers, so do informal jobs. At-risk employment is sharply reduced to less than 15% of the baseline during a recovery led by the informal sector, closing the gap with the US.

The mechanisms and dimensions of employment exposure to the crisis considered in our framework explain over 72% of the cross-sector variability of actual employment and income losses observed in the three countries in the second and third quarter of 2020. Informal employment, more negatively affected than formal employment at the onset of the crisis, also recovered faster.

Our model offers an easy-to-implement diagnostic tool to quantify the relative vulnerability of jobs and families' incomes to shocks in different economies, on the basis of their differential economic and labor structures.[3] As such, it also offers information that is vital to policy makers in deciding policy responses to crises and can be easily implemented in other countries,[4] and in other contexts, by adapting the set of shocks that are considered.

[3] Actual job and income losses will be mediated by other shocks, including, for example, policy responses which can be designed on the basis of our framework's diagnostics.

[4] See IMF's Western Hemisphere's *Regional Economic Outlook* for an application of our framework (IMF, 2020).

Our work relates to a broader literature that aims to understand the role of firm heterogeneity in aggregate activity. Researchers have documented that in less-developed economies the firm-size distribution is more concentrated in the lower left-hand tail (Tybout, 2000; Poshke, 2018; Bento and Restuccia, 2020). This paper explores important economic and policy implications of the left-skewness of the firm-size distribution.

Compared to other studies of the aggregate economic consequences of COVID-19, three features of our work stand out. First, we focus on how the structure of emerging economies affects the economic consequences of the crisis. As such, our work relates to pieces that highlight the vulnerability to the crisis implied by the high prevalence of informality (Leyva and Urrutia, 2021; Alon et al, 2020) and of small firm employment (Guerrero-Amezaga et al, 2022). Leyva and Urrutia's work recovers productivity and labor supply shocks from the data through the lens of a structural model. In a complementary methodology, we take observed shocks and treat the data with them. In doing so, we uncover the relative roles played by long-lasting stay-at-home orders vs. sector-specific demand shocks.

A second noteworthy feature is that, in our setting, lockdowns are found to play a larger role in generating economic risk than does the effect of fear on demand. This is in contrast to previous findings of a much stronger effect from fear-driven demand contractions than from lockdowns, relying on the differential timing of shelter-in-place orders across regions of the United States for identification (e.g., Goolsbee and Syverson, 2020) or on simulations that consider lockdowns much shorter in duration than those experienced in several EMEs, including Argentina, Colombia and Peru. US shelter-in-place orders during 2020 were typically limited in duration and in geographic coverage, and much less stringent than the blanket long-duration lockdown on all non-essential productive activity that we simulate. They were also preceded, and arguably triggered, by increased contagion. A different strand of the literature postulates models that simulate contagion and assume a demand response to it. Early lockdowns, such as the one in Colombia and in our simulation, preceded contagion, and thus contagion-driven demand contractions, by several months.

Finally, by contrast to the already vast theoretical literature on the COVID-19 crisis (e.g., Acemoglu et al. 2020, Alfaro et al. 2020, Atkenson 2020, Baqaee and Farhi 2020a,b), we measure economic risk—rather than forecasting actual economic and health effects—and do so using a simple probabilistic framework. The framework is sufficient to quantify relative exposure given different economic structures, and it allows us to abstain from projecting the spread of the disease. Aside from the potential controversy surrounding the modeling and identification of behavioral responses, any such model employs parameters on the spread of the disease, which are imprecise in general and even more uncertain in contexts where COVID testing remained low for extended periods. As such, our work more closely resembles the empirical literature on the evolution of the labor market and employment trends during the COVID-19 pandemic (Coibion et al. 2020).

Section 2 presents our framework and explains how we implement it. Section 3 presents our

benchmark results on differential job and income vulnerability in Argentina, Colombia and Peru and a counterfactual advanced economy. Section 4 assesses the extent to which the dimensions incorporated in our model explains cross-sector variability in ex-post observed job and income losses. The final section discusses policy implications.

2 Empirical Framework and Implementation

2.1 Framework

A worker who before the pandemic had a job i in sector s faces a probability π_{ist} of losing her job due to the pandemic in a given scenario t. In absence of policies to mitigate job and income losses, π_{ist} is the joint probability that (pre-pandemic) job i is in a sector hit by one or several COVID-associated shocks and at the same time is not isolated from their effect by attenuating attributes. Specifically:

$$\pi_{ist} = \pi_s \times (1 - \pi_{it}) \times (1 - T_i)\,, \tag{1}$$

where T_i is the probability that i is in an occupation that allows the worker to work from home; π_{it} is the probability that job i is sustained even if the employer's revenue is hard hit by shocks and the worker cannot work remotely, which is allowed to vary across scenarios indexed by t;[5] and π_s is the probability that sector s is affected by the shocks associated to the pandemic.

More specifically, π_s is the joint probability that output in sector s is affected by supply (lockdown) and/or demand shocks, either directly or indirectly via input-output linkages with sectors directly hit:

$$\pi_s = Prob\,(Lock_s = 1 \cup Dloss_s = 1 \cup IO_s = 1)\,. \tag{2}$$

$Lock_s = 1$ denotes a collapse of supply in sector s due to a lockdown ordering its on-site operations to stop; $Dloss_s = 1$ a demand collapse for sector s due to changes in behavior by consumers not driven by lockdown orders; and $IO_s = 1$ an output collapse in s due to demand and lockdown shocks in downstream and/or upstream sectors, such that:

$$\begin{aligned} Prob\,(IO_s = 1) = &\sum_{j \neq s} Prob\,(Lock_j = 1 \cup Dloss_j = 1) \times \frac{purchases_{j:from:s}}{grossout_s} + \\ &\sum_{j \neq s} Prob\,(Lock_j = 1 \cup Dloss_j = 1) \times \frac{purchases_{s:from:j}}{grossout_s}, \end{aligned} \tag{3}$$

where $\frac{purchases_{j:from:s}}{grossout_s}$ represents the share of sector s gross output purchased by sector j.

[5] We explore different scenarios of susceptibility of formal vs informal jobs and in smaller vs. larger firms

The number of jobs actually lost in scenario t due to the pandemic is given by:[6]

$$Job\_loss_t = \left(AD \times \sum_i \pi_{ist} \right) \times \varepsilon_t \tag{4}$$

$$= Jobs\_at\_risk_t \times \varepsilon_t. \tag{5}$$

In equation (5), AD is a standard Keynesian multiplier and ε_t captures unmeasured factors, including, but not necessarily limited to, endogenous policy responses and measurement error. $Jobs\_at\_risk_t$ is our main object of interest. We also use the model to obtain a measure of value added at risk, explained in section 3.

2.2 Data and Implementation

Our main sources of data are the Household Surveys for Argentina, Colombia, and Peru for 2019. We now describe how we measure each of the terms in equation (1) using these data:[7]

π_{it}: We take into account two different attributes that affect job vulnerability to COVID shocks: formal/informal status and employer size.

Formal workers are covered by employment protection legislation (EPL) that prevents them from being discharged unless specific circumstances are met. In the longer run, however, the high costs to the employer of formal contracts imposed by EPL and the greater flexibility of informal jobs may overturn the table in favor of informal jobs.[8] In turn, larger firms are more likely to access funds that may allow them to keep contracts going during periods of financial stress. They may also have more effective access to government subsidies (Guerrero-Amezaga et al., 2022).

We define a job as formal if it complies with social security contributions (see Appendix for country specific details). We thus distinguish labor informality from employment in microestablishments and from self-employment, although they are highly correlated.

We explore three different scenarios for π_{it}. In $t = 1$, π_{it}=0 for jobs that are either informal or in micro-enterprises (up to 10 employees) and π_{it}=1 for all other jobs. This captures the view that informal workers, not covered by EPL, and those in firms so small that it was impossible for them

[6]Explicitly, equation (2) is calculated as:

$$\pi_s = Lock_s + Dloss_s + IO_s - Lock_s \times Dloss_s - Lock_s \times IO_s - Dloss_s \times IO_s + Lock_s \times Dloss_s, \times IO_s$$

Joint products between $Lock_s$, $Dloss_s$, and IO_s capture that several catastrophic shocks, each able to make the sector collapse, could occur simultaneously. Think of hotels during blanket lockdowns concurrent with contagion peaks at the onset of the crisis: costumers could not reach hotels due to constraints to mobility, but even in absence of such constraints many costumers would have avoided hotels.

[7]For further details, see the Appendix.

[8]For instance, Colombian authorities were reluctant to authorize layoffs and dismissals at the beginning of the crisis. However, some were authorized a few months into the crisis. Replacing those lost jobs with formal ones is more difficult than replacing them with self-employment or informal contracts

to access the additional resources necessary to keep payrolls going under strict lockdowns, are the most exposed to the effects of COVID shocks. Scenario $t = 2$ is similar to scenario 1, but it extends π_{it}=0 from micro to other small firms (all those with up to 50 workers), with the idea that even firms of this size may be resource-constrained, or at least become resource-constrained as the crisis elapses. Finally, scenario $t = 3$ quantifies losses under the alternative view that it is formal jobs that are at greater risk given the larger costs of creating formal than informal jobs. We see this as a scenario better fit to capture medium-run effects, when informal jobs have begun to bounce but the creation of new formal jobs is held back by the rigidity that affect the formal segment. It could also represent contexts where informal jobs circumvent restrictions (as in Alon et al 2021).

π_s: We set $Lock_s = 1$ for all non-essential sectors, since our data cover the first two quarters of the pandemic, a period in which Argentina, Colombia and Peru implemented blanket lockdowns banning all on-site work for non-essential sectors of activity. Appendix Table A2 lists the sectors considered by the government as essential and non-essential, using the ISIC rev. 4 two digit classification.

We estimate $Dloss_s$, defined as the proportional revenue contraction in the sector that would have occurred in the absence of lockdown orders, by taking advantage of the fact that Sweden did not impose lockdowns in the early phases of the COVID-19 crisis. We take the proportion of output lost in Sweden by sector in the second quarter of 2020, $\Delta Y_s^{Sweden}/Y_s^{Sweden}$ and recover from equation (1) the level of $Dloss_s$ that would be compatible with $\overline{\pi}_{st} = \Delta Y_s^{Sweden}/Y_s^{Sweden}$ if $Lock_s$=0 for all s, where $\overline{\pi}_{st}$ is the average of π_{iset} over workers in sector s. We use the Swedish IO matrix to calculate IO_s for Sweden, and the Swedish distribution of income to calculate the relevant AD multiplier, see below for details on the construction of AD and IO_s. For T_s^{Sweden}, we use the fraction of workers who are able to telework in an advanced economy, calculated from the United States' ACS using Dingel and Neiman's classification.

T_i: Our measure of the probability that i is (at the onset of the crisis) in an occupation that allows her to work from home is based on Dingel and Neiman (2020). Following the procedure described in the Appendix, T_i is the fraction of ACS US workers, in i's occupational category, whose original (US) occupational class was designated as fit for remote work. As discussed in connection with Figure 1, the fraction of US workers in occupations suited for remote work is larger than in the selected countries (37% versus about 30%), even without factoring in much greater access to the internet and computational literacy in the United States.

To compute the indirect supply and demand shocks IO_s, we supplement Household Survey data with information of IO matrices, as reported by the OECD for Argentina and Peru and the Colombian Statistics Bureau.[9] We use the IO matrix to calculate $\frac{purchases_{j:from:s}}{grossout_s}$ and $\frac{purchases_{j:from:s}}{grossout_s}$.

As for the aggregate demand multiplier, in the absence of reliable estimates of the MPC, we

[9] In all three cases the IO matrix uses a slightly higher level of aggregation than the ISIC two-digit classification system.

rely on the estimates of MPC by quintile of income (MPC_g) in the United States as reported by Carroll et al. (2017), and compute the country's MPC as the weighted average of the MPC by quintile, weighted by the fraction of workers in Argentina, Colombia, and Peru whose income (adjusted by PPP) fall within each US income bracket. That is

$$AD = \sum_Q \rho_Q \times \frac{1}{1 - MPC_Q} \tag{6}$$

where subindex Q indexes income quintiles in the US; rho_Q is the fraction of workers in the respective Latin American country whose income falls in the (PPP adjusted) range of incomes for Q in the US; and MPC_Q is Carrol et al's estimate of the Marginal Propensity to Consume in US households in quintile Q.

Over 90% of urban workers in Argentina, Colombia, and Peru report PPP adjusted income levels that fall in the lowest quintile of the U.S. distribution. The resulting AD multipliers are 1.688, 1.676, and 1.675 for Argentina, Colombia, and Peru.[10]

3 Economic Exposure Under Different Economic Structures

This section quantifies the exposure of employment to the crisis under a strict lockdown where all non-essential activities are banned. The Appendix quantifies exposure under a less stringent lockdown, eased to allow manufacturing and construction to open, as happened in Colombia, Argentina and Peru after June 2020.

Jobs and value added at risk. The upper panel of Figure 2 presents the results for $Jobs\_at\_risk_t$ (equation (5)) for the three different scenarios t defined in section 2.2. Our baseline analysis, which we view as best representing the onset of the crisis, is for scenario $t = 1$, where jobs that are informal or in micro-enterprises are at risk.

The bars labeled "Argentina," "Colombia" and "Peru" use the countries' actual distribution of jobs in 2019 across firms, sectors and occupations. An astonishing 47% of Argentinian and Peruvian workers, and 48.3% of Colombian workers, face potential job loss in the baseline scenario. We run an alternative simulation in which we change the sample weights from the household survey of each of the three countries to emulate the distributions of firm size, industries and occupations in the US economy, assuming that all employment in the US is formal.[11] Imposing the US economic structure on our three countries yields an employment exposure of just 9.8%, one-fifth of the risk measure

[10] It is difficult to get reliable MPC estimates for developing economies. Hong (2020), an exception, estimates an even larger average MPC of 0.632 for Peru. Under this estimate, our baseline results are a lower bound for employment vulnerability in Latin America.

[11] The US' employment by occupation distribution is from the American Community Survey, 2017; and the distribution of employment across firm sizes and sectors from the Business Dynamics Statistics.

obtained for Latin America (bars labeled "US structure").[12]

When firms with up to 50 employees are included ($t = 2$) , the number of jobs at risk increases by around five p.p. in Argentina and Colombia (to 52.6% of workers in Argentina and 52.8% in Colombia) and by 1.9 p.p in Peru (to 48.9%). The mild increase in estimated exposure that results from adding firms between 11 and 50 employees demonstrates that most vulnerability is associated with tiny firms of fewer than 11 workers. Under the US structure, a more substantial increase of from 9.8% to 24.9% is observed when including firms between 11 and 50 employees, still far from the risk of job loss from the crisis under the Latin American economic structure but with a lesser gap with respect to these economies than in scenario $t = 1$. The fact that the gap between the US and Latin America simulations is so strikingly reduced when adding firms of 11-50 workers (from one-fifth to one half) further illustrates the magnitude of the higher and more immediate economic and social costs to which EMEs are exposed given the predominance of micro-enterprises.

Our third scenario ($t = 3$), shown in the third set of bars in Figure 2, is a scenario that could represent what occurs after the first few weeks or months of a crisis that initially hits informal workers and micro-enterprises the most. After that period, necessity may fuel the generation of informal and self-employed jobs, in the context of low adjustment costs for these segments, while the creation of new formal jobs in small and micro firms faces high relative costs. Jobs at risk are dramatically reduced to 14.7% of workers in Argentina, 12.3% in Colombia and 6% in Peru, compared to the much higher 24.9% under the US' economic structure. Lesser risk to employment in the recovery under the prevalence of flexible informal employment that characterizes Latin American labor markets, however, is a bitter victory, because a recovery biased toward informality would imply an impoverished post-crisis employment structure in Latin America, and therefore lower income gains. Section 4 shows that, indeed, after an initial stronger blow to informal jobs and those in micro-enterprises, these segments recovered at a faster pace.

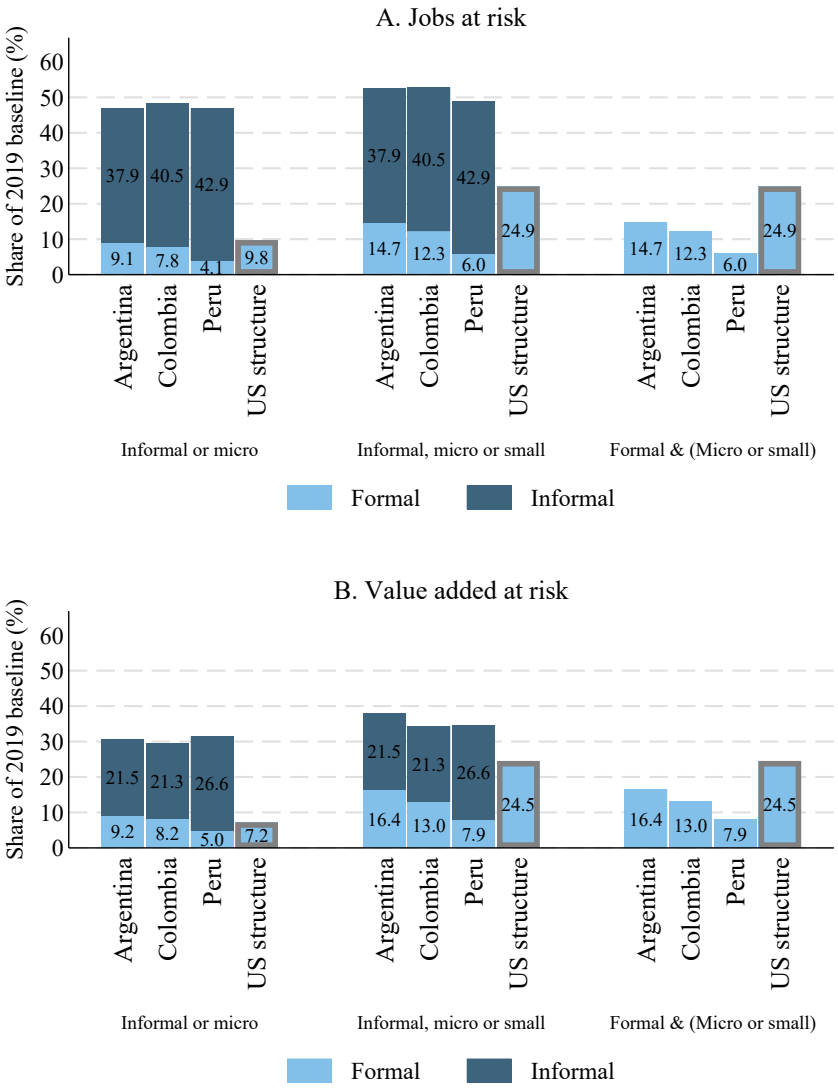
In the three scenarios, differences between Latin America and the counterfactual US are mostly driven by the incidence of informality and self-employment, as indicated by the formal/informal breakdown in Figure 2. Because informal jobs and tiny firms tend to carry low-skilled activities, income (value-added) exposure is lower than that of jobs. Figure 2, reports value added at risk, computed as:

$$Value\_at\_risk_t = \left(AD \times \sum_s \frac{VA_s}{W_s} \left(\sum_i (\pi_{ist} \times w_{ist}) \right) \right) \tag{7}$$

where w_{ist} is the income of worker i who works in sector s. VA_s is value added in sector s and W_s is labor income in sector s, both from the IO matrix. Figure 2 shows that 30.7% of monthly value added is at risk in Argentina, 29.5% in Colombia, and 31.6% in Peru in the baseline simulation. This stands in contrast to only 7.2% in the counterfactual modeled on the US economic structure. If

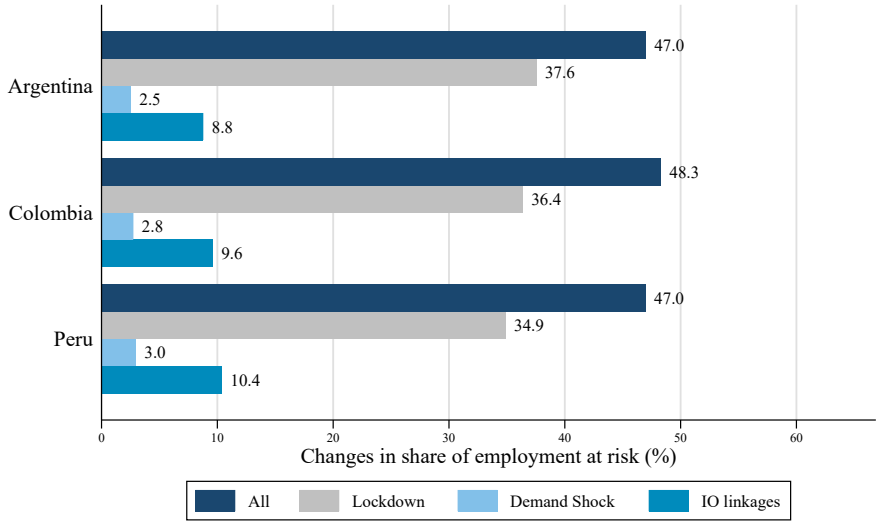
[12]This figure corresponds to the weighted average across counterfactual results in each of the three household surveys, where each country is weighted by its number of workers in 2019

Figure 2: Jobs and value added at risk: total lockdown



Note: This figure estimates jobs at risk and value added at risk under alternative scenarios of firm size and employment categories affected by the shock. The first set of bars in each graph represents a scenario in which informal jobs and those in micro firms (<10 employees) are affected. The middle set of bars adds jobs in small firms (10-50 employees). In the right-hand set, informal jobs are not affected or have already recovered. Bars labeled "U.S. structure" represent jobs at risk and value added at risk under the assumption that the distribution of workers is identical to that of the United States in terms of economic sectors, firm size and occupation. The numbers shown correspond to the average of the simulation results for Argentina, Colombia, and Peru assuming the distribution of employment in the US, weighted by the number of workers in 2019 taken from each country's Household Surveys.

Figure 3: Jobs at risk by source of shock



Note: This figure estimates jobs at risk by source of the shock. It refers to the simulation in which informal jobs and those in micro firms are affected (the left-hand set of bars in Figure 2). The impact of each source (lockdown, demand, IO linkages) is calculated as the difference in the jobs-at-risk measure that results from shutting down each source.

we consider firms of up to 50 workers, the numbers grow by 7.2 p.p. in Argentina, 4.8 in Colombia, and 2.9 p.p. in Peru, and a much higher 17.3 p.p. in the counterfactual US case.

The Role of Shocks: Lockdowns and Demand. Figure 3 displays the differential contributions of lockdown, demand shocks and amplification effects due to linkages and a demand multiplier. The contribution of each shock source is calculated as the impact on our risk measure of setting that shock to zero in equation (5). Lockdowns explain the largest share of the effect: excluding them reduces the estimated jobs at risk by 33.3 pp on average across the three countries, to less than 13%. Meanwhile the effects of IO-transmitted shocks and direct sector-level demand shocks are more modest: reductions of 9.6 pp and 2.76 pp, respectively on average for the three countries.[13]

Demand shocks are more important in both absolute and relative terms when considering a less extreme lockdown scenario that excludes industrial activities (as was the case in Colombia in the third quarter of 2020), as reported in the Appendix. Though this version of lockdown is milder, it is still stringent enough that more than 40% of jobs are at risk, and the lockdown effect widely dominates the total effect: (24.3 of the 40 pp are explained by the lockdown). Figure A7 in the Appendix shows that changing the underlying economic and labor structure to that of the United States does not significantly change the relative weight of the different shocks in the magnitude of

[13]The three individual effects add approximately to the total because of the cross interactions in equation (5).

jobs at risk.

4 Variance Decomposition

We now contrast the quantitative implications of our framework with actual labor outcomes during the second and third quarters of 2020. This is the period of nation-wide lockdowns in the three countries, although as mentioned by the third quarter some sectors were progressively allowed to return to on-site production.

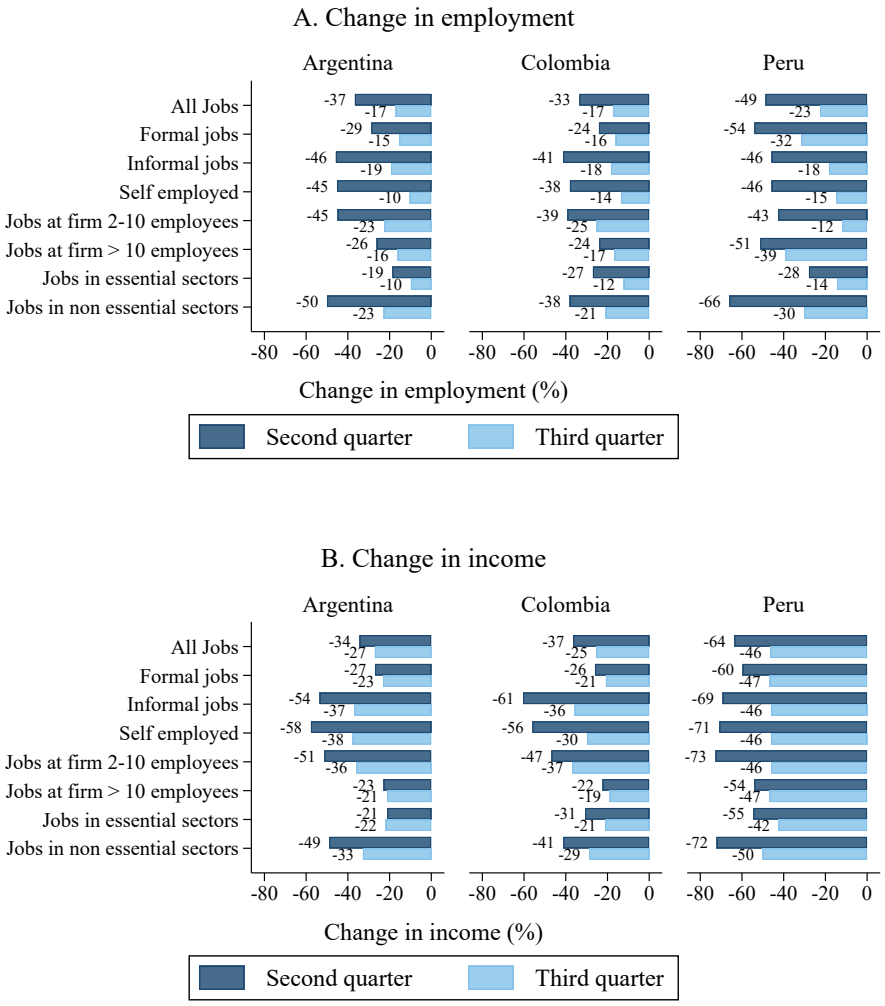
Figure 4 summarizes actual losses of jobs and income. The upper panel considers jobs in which the person reported having worked a positive number of hours.[14] Relative to the second quarter of 2019, 36.7% of jobs were lost in the same quarter of 2020 in Argentina, 33.4% in Colombia, and 48.7% in Peru. These losses are equivalent to over 70% of the estimated jobs at risk in our $t = 1$ scenario in the three countries. For Peru, in fact, they correspond almost identically to the number of jobs at risk. As captured by equation (4), actual jobs lost are not identical to jobs at risk because of endogenous policy responses and measurement error, and, potentially, other unmeasured factors.

Consistent with the idea that informal jobs and those in tiny firms are hit hardest at the onset of the crisis (our $t = 1$ scenario) informal work and salaried employment in tiny firms were most severely affected at the beginning of the crisis. In particular, job and income losses in the second quarter of 2020, when the crisis started, were much larger for informal than formal jobs and for workers self employed or in businesses of at most 10 employees than for those in larger firms. The gap is large in terms of jobs, and even larger in terms of income. In Argentina, in terms of jobs, losses are 45.8% in informality vs. 28.8% in formality, while in terms of income they are 53.6% vs 27% for informal vs. formal. For Colombia, the numbers for informal vs. formal are 41.3% vs. 24.1% in terms of jobs and 60.5% vs. 26% in terms of income. Peru shows a milder gap in terms of income 69.3% vs. 59.7%, and a gap of the opposite sign in terms of jobs: more job interruptions took place among formal than informal jobs at the beginning of the crisis. This apparent anomaly in the Peruvian data compared to the other two countries is in part due to higher temporary layoffs of formal workers compared to informal workers in this country: initial informal job losses are larger than formal job losses if we take into account all workers who report having a job, independent of whether they worked a positive number of hours, as shown in Figure A8.

The ex-post evidence is also consistent with the expectation of more rapid recovery of informal jobs vs. formal jobs. Comparing the third quarter of 2020 to the second quarter, losses in the informal sector retract markedly. While there is also improvement for formal jobs between the second and the third quarters, it is mild. Consistent with our assumptions about exposure, employment in

[14] The report of hours worked corresponds to the week prior to being interviewed. In the second quarter of 2020, this percentage jumped due to temporary layoffs and halted business activity at the employer. In Colombia, it reached 15%, returning to its normal levels of around 3% by the third quarter of 2020.

Figure 4: Employment losses: Second and third quarters, 2020 vs. 2019



Note: Losses shown are for a given period of 2020 and the same period of 2019. We take into account only active jobs, defined as those in which the worker reported working a positive number of hours in the previous week.

non-essential sectors (subject to the lockdown) fell much more in essential vs. non-essential sectors. In Argentina and Peru, job losses in essential sectors more than doubled those of non-essential ones (50% vs 18.7% and 66% vs 27.9%, respectively, in Argentina and Peru in the second quarter). The gap is milder but sill large in Colombia: 38.2% vs. 29% in the second quarter. Both types of sectors show signs of recovery in the third quarter, but this is more marked for essential sectors, impacted by lockdowns and therefore by the progressive easing of restrictions.

To assess more formally the ex-post role played by the various shocks and dimensions of economic exposure that we model, in explaining the observed labor-market outcomes, we decompose the cross-sector variance of losses. We do so by regressing observed employment losses at the sector level (denoted by ΔE_s) against the shock and exposure measures considered in equation (1): the dummy for non-essential sector (subject to the lockdown, L_s); the estimated demand shock (D_s); the estimated indirect lockdown and demand shocks via IO linkages (IO_s^L and IO_s^D); including interactions with the share of total sector employment unsuited to work remotely $\left(1-\bar{T}_s\right)$, as well as those that are informal, self-employed or in firms with 10 or fewer workers (S_s). In particular, we run the following reduced form regression from our model:

$$\begin{aligned}\Delta E_s =& \beta_0 + \beta_1 L_s + \beta_2 D_s + \beta_3 IO_s^L + \beta_4 IO_s^D + \beta_5 (1-\bar{T})_s + \beta_6 S_s + \\ & \beta_7 L_s \cdot (1-\bar{T})_s + \beta_8 D_s \cdot (1-\bar{T})_s + \beta_9 IO_s^L \cdot (1-\bar{T})_s + \beta_{10} IO_s^D \cdot (1-\bar{T})_s + \\ & \beta_{11} L_s \cdot S_s + \beta_{12} D_s \cdot S_s + \beta_{13} IO_s^L \cdot S_s + \beta_{14} IO_s^L \cdot S_s + u_s\end{aligned} \tag{8}$$

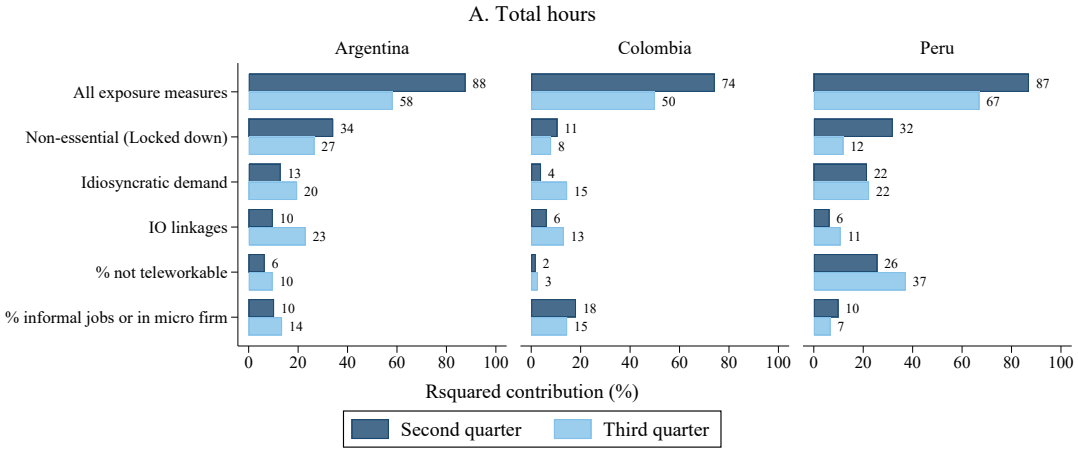
We report the R-squared statistic for regression (8). To assess the separate weight of each of these factors, we exclude them one by one from the regression. The contribution of a given factor is calculated as the decrease in the regression's R-squared when excluding that factor. While this fails to take into account cross correlations between the determinants of losses that we measure, it gives us an idea of the expost importance of each separate factor. Results are presented in Figure 5.

Our sector-level measures of shocks and exposure explain a very large fraction of total cross-sector variability in employment losses and labor-income losses. Employment losses are measured in terms of total work hours lost, to take into account the intensive margin. In the second quarter, this empirical model explains 87.7% of the variance of total hours lost for Argentina, 74.2% in Colombia and 87% in Peru. Dropping one determinant at a time, we find that lockdowns are the single factor with greatest explanatory power, except in Colombia where they are second to the prevalence of informality and jobs in tiny firms. In Peru, the fraction of workers with occupations not fit to work remotely also carry a large weight. The demand shock is important, but the combination of lockdowns plus informality/micro-entrepreneurship, without taking demand into account, explains over 65% of second-quarter variation.[15]

The explanatory power of our equation 8 is a little lower in the third quarter, when mobility

[15] Total Rsquared minus the contribution of demand

Figure 5: % of variance in job losses explained by measures of shocks and exposure



Note: This figure reports the R-squared from regression (9) (the first set of bars), and the contribution of each regressor to that R-squared (the remaining bars). The contribution of a given regressor is given by the difference between the R-squared of regression (9) the R-squared excludin that regressor. Source: Authors' calculations, based on employment losses reported in each country's household survey for the second and third quarters of 2019 and 2020.

restrictions started to be eased, compared to the second quarter. The lockdown indicator is the factor that losses individual explanatory power. While the lockdown becomes less important, the demand shock actually increases its contribution to the R-squared, especially in Argentina and Colombia.

5 Discussion and Conclusions

We show that the adverse combination of high informality and micro-entrepreneurship with early strict blanket-lockdowns accounts for over 65% of work-hours lost in the second quarter of 2020 in LAC. Our work points to the high costs for many EMEs of containment strategies based mainly–or even solely–on long-term lockdowns, much higher than in Advanced Economies. Lockdowns, of course, also slow contagion, potentially mitigating the collapse of the demand. Given that EMEs' economic exposure is high relative to advanced economies, and that the ammunition available to mitigate economic impacts is limited, their governments bear a large responsibility to assess the costs and benefits of their options more carefully than other countries. At this point, the most effective alternative to blanket lockdowns is to quickly scale up vaccinations. Latin America, with the exception of Chile, initially lagged behind in vaccination campaigns and has slowly caught up. Efforts to increase vaccination capabilities in the region have started to materialize (e.g. in Brazil),

but will remain difficult for these relatively weak states. Nevertheless, the cost of lockdowns dwarfs these difficulties.

The pandemic has also prompted debate on how best to support workers and firms. There have been calls to increase access to unemployment insurance, to provide cash transfers to vulnerable populations, and to preserve formal employer-employee relationships by subsidizing some payroll costs (OECD, 2020). All of these options would probably generate large returns, but they are difficult to implement and finance in the EME context; priorities must be carefully established. Loss of income among informal workers, a population that typically lacks savings, constitutes the most pressing concern. These losses are best addressed via direct income transfers, which have been implemented in many countries in the region. As the crisis persists, the need to reduce barriers to formal jobs becomes more urgent.

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Emerging Economies and COVID-19
Shutting Down in a World of Informal and Tiny Firms
Online Appendix

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Online Appendix

A Data details

Our main sources of data are the Household Surveys of Argentina ("Encuesta Permanente de Hogares" – EPH), Colombia ("Gran Encuesta Integrada de Hogares" – GEIH), and Peru ("Encuesta Nacional de Hogares" – ENAHO) for 2019, collected by the Bureau of Statistics of each country.

The three datasets are the basis for official statistics on the labor market and are representative at the national and urban level (Colombia and Peru), and at the urban level (Argentina). In all three cases, anonymized version of the datasets are available on the respective Bureau's website.

Along with the general classification of the working-age population among employed, unemployed and out of the labor force, the surveys collect information of job characteristics that we use for our analysis. For those employed, the surveys record the person's class of worker (employed, self-employed, employer or unpaid worker), the job's economic sector (using the four-digit ISIC revision-4 classification system for Colombia and Peru and the CAES classification system for Argentina); whether the person is salaried or self-employed; the size of the firm in which she works, in terms of categories of number of workers; and her occupation, following each country's national occupation classification.

The survey also includes information to classify a worker as an informal worker. In Peru, there is an official definition reported in the dataset that considers a person as informal if either she works in a low productivity unit or her job lacks basic social security coverage. In Argentina and Colombia, the surveys record information about whether the worker and her employer comply with pension contributions. For Argentina, we label a job as informal if it is a salaried job that does not comply with pension contributions or if the worker is a self-employed worker with less than post-secondary level of education. For Colombia, we label a job as informal if does not make mandatory pension contributions. In Colombia, information about formality and firm size was not collected in April, as a result of emergency adjustments to the survey collection in the early phase of the nation-wide lockdown.

Using these variables, we construct our measures of job vulnerability at the individual level following the procedure described in Section 2. Most of the variables used in the analysis are taken directly from household surveys, except for our measure of ability to work from home. We construct our measure that a person is (at the onset of the crisis) in an occupation that allows her to work from home is based on Dingel and Neiman (2020). They classify 478 occupational categories in the American Community Survey (ACS) as either suited to work from home or not.

As we illustrate in Table A1 for Colombia, non-compliance with mandatory contributions to the pension system is often related to non-compliance with other mandated contributions (to the health-care system, occupational health and safety, etc.).

Because Argentina, Colombia and Peru use different occupational classifications, we adapt those classifications to ISCO-08 using available crosswalks, and aggregate Dingel-Neiman classes to the level of ISCO-08 occupational categories (2 digits). Since the grouping from this procedure is less granular than Dingel-Neiman's classification by occupation, we define the probability the a person is in an occupation that allows her to work from home as the fraction of ACS US workers by occupational category, whose original (US) occupational class was designated as fit for remote work.

Figure A1: Number of Covid-19's confirmed deaths per million inhabitants

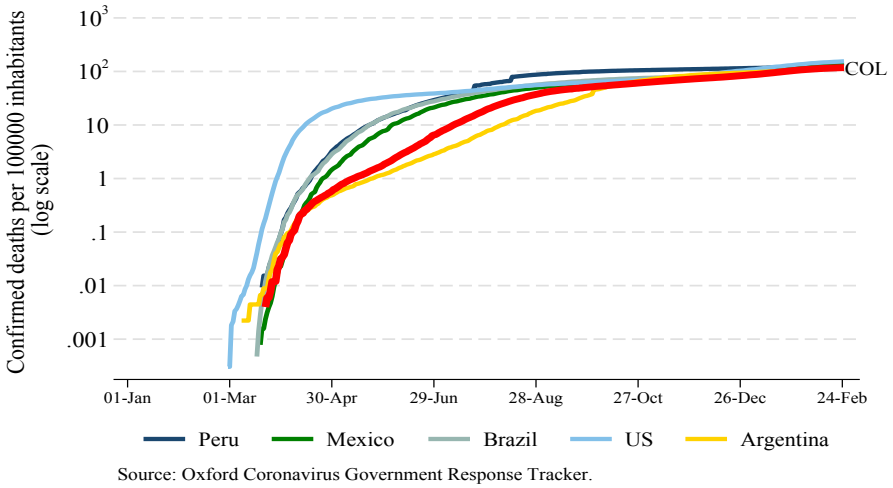


Figure A2: Coronavirus Government Response Index for selected countries in the Americas

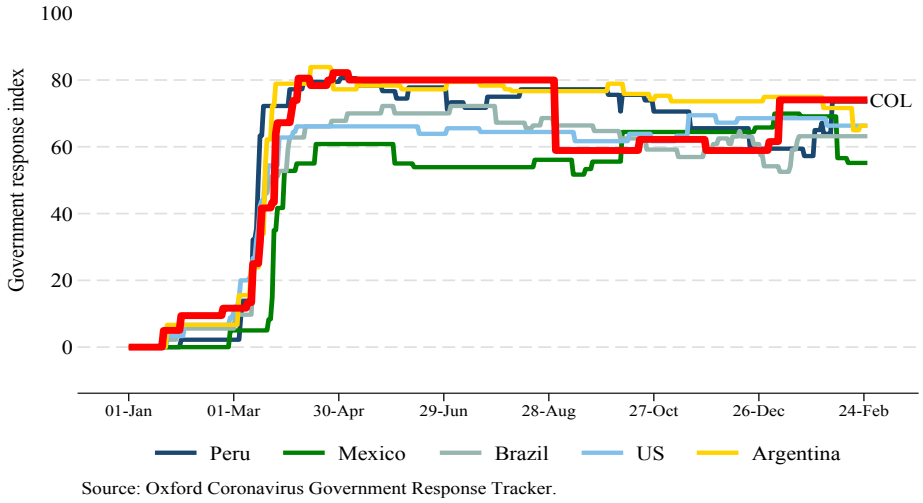
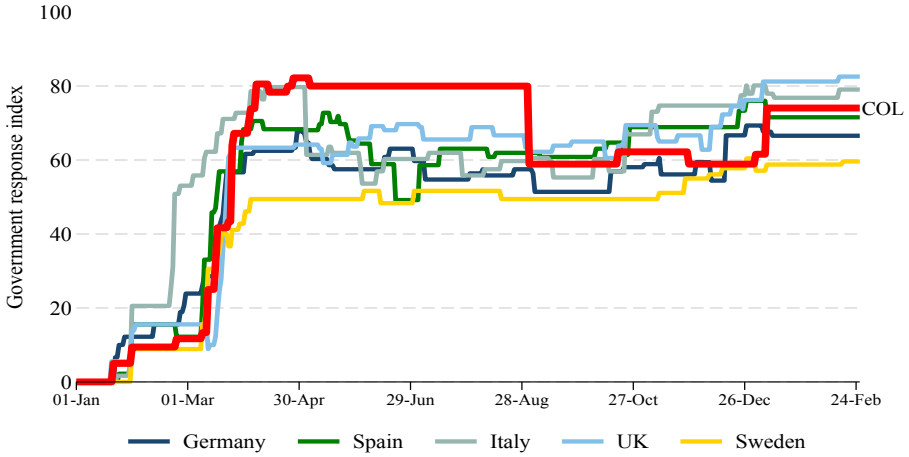
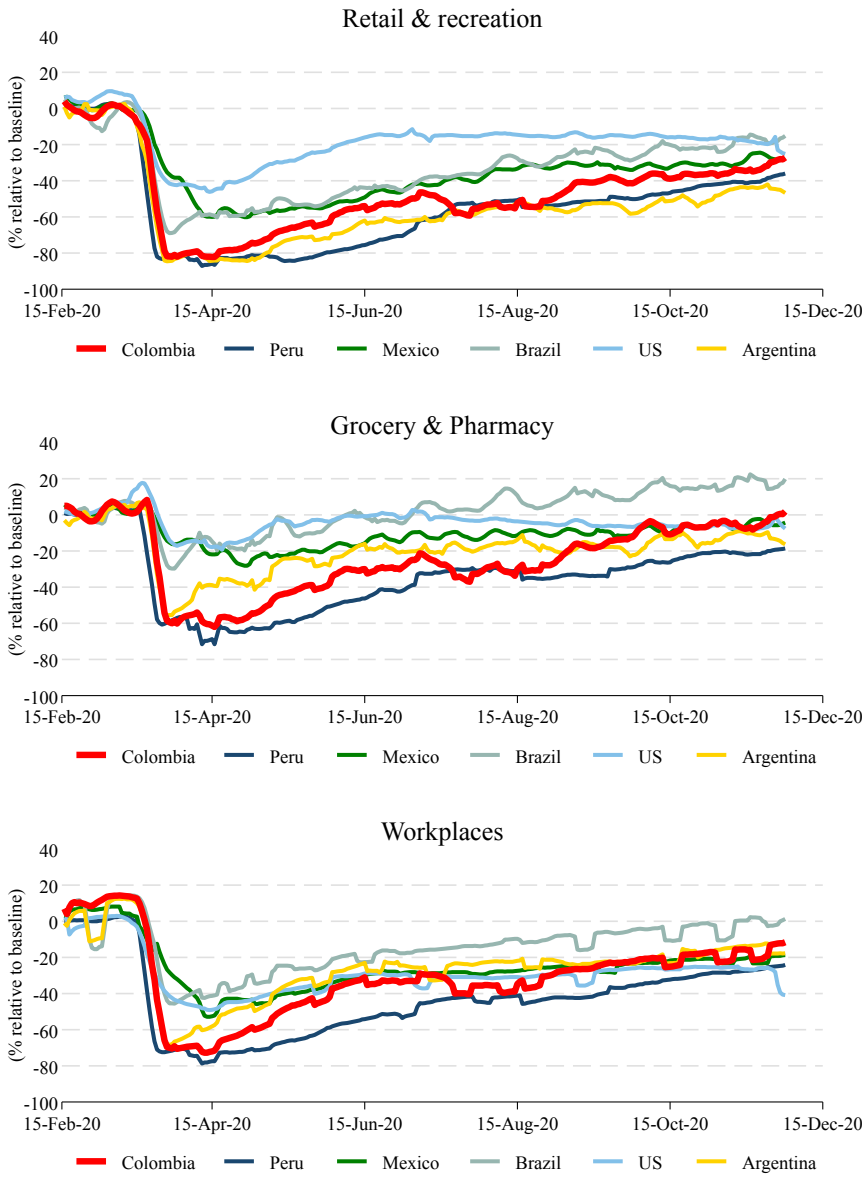


Figure A3: Coronavirus Government Response Index for selected countries: Colombia vs. Western Europe



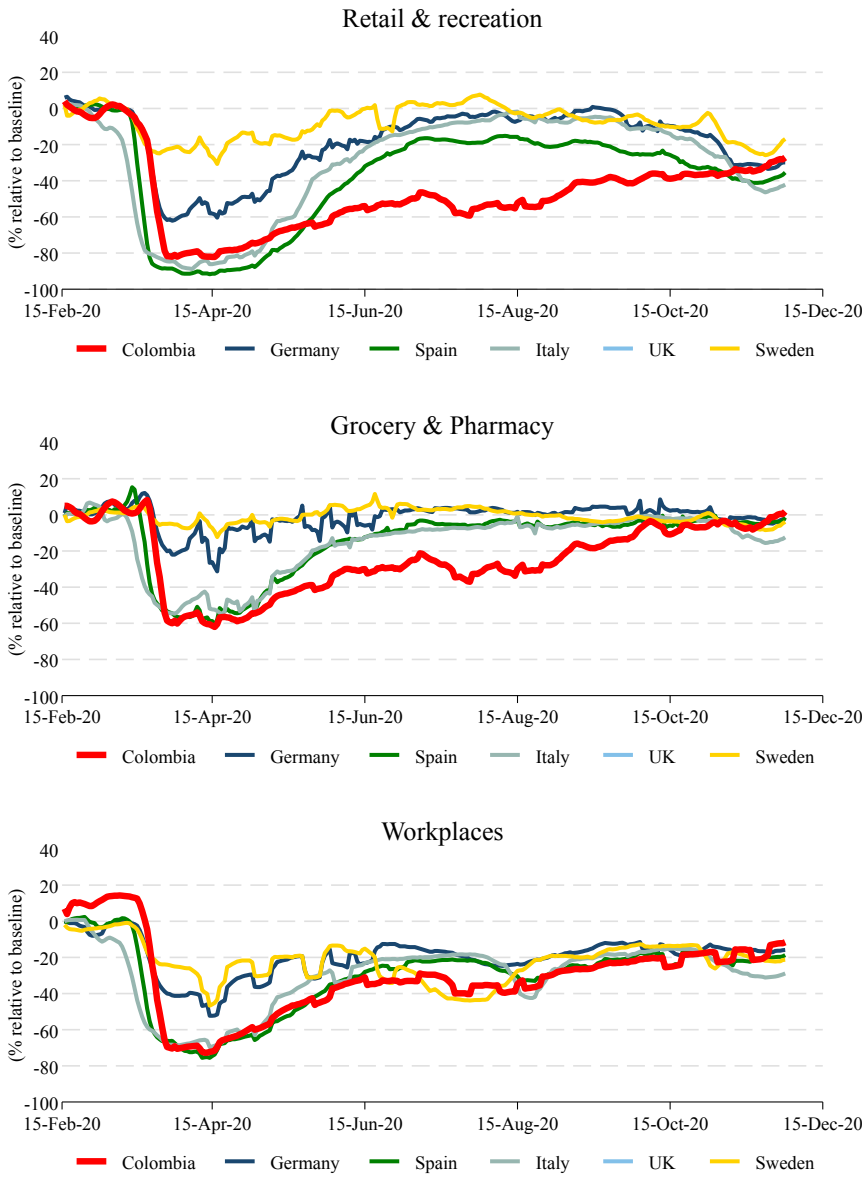
Source: Oxford Coronavirus Government Response Tracker.

Figure A4: Mobility trends for selected countries: Colombia vs. the Americas, 2020



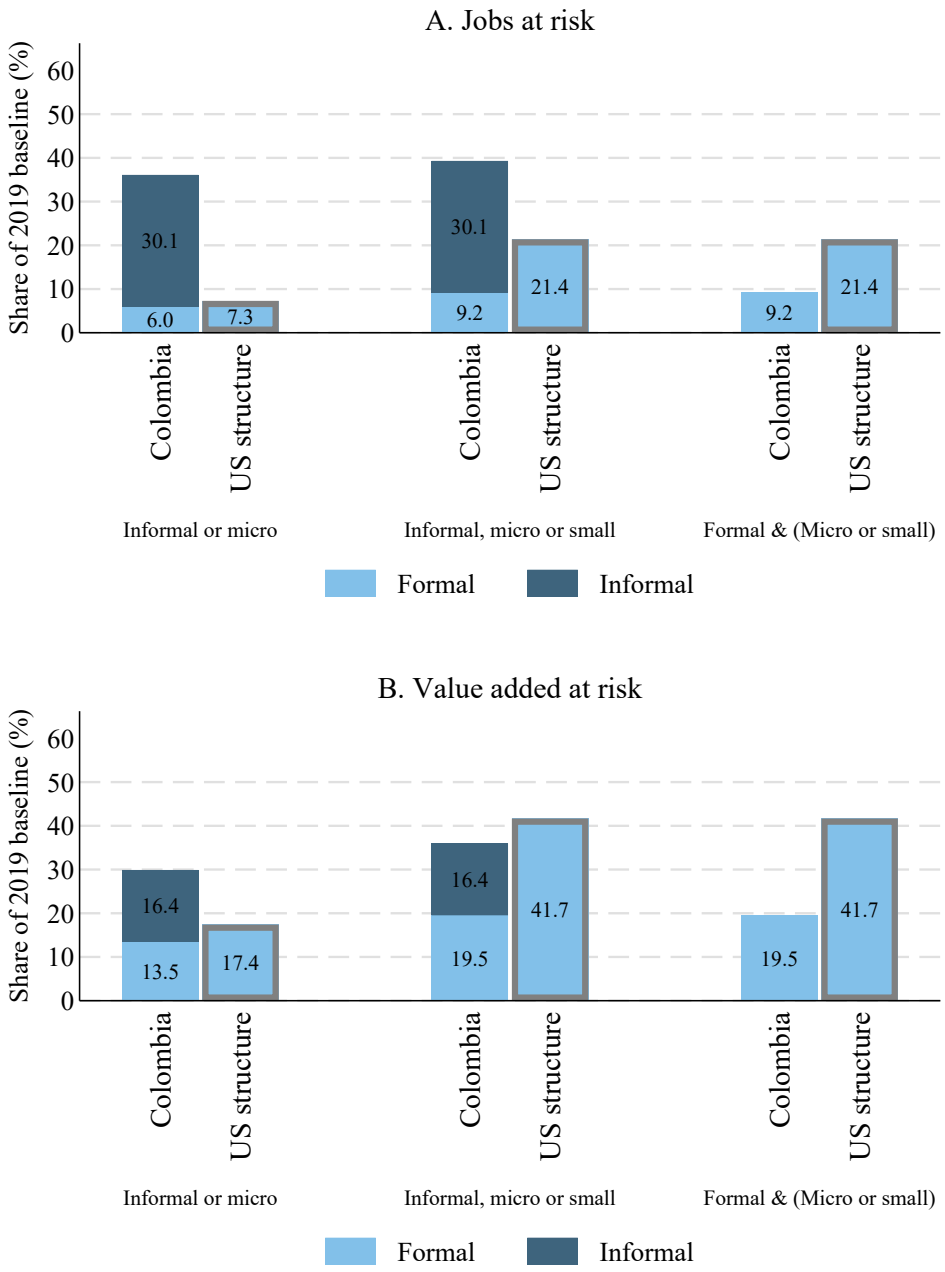
Note: The figure shows patterns in mobility as reported by Google Mobility. The baseline is the median value for the same day of the week between 3 January–6 February, 2020. Source: Google's COVID-19 Community Mobility Report.

Figure A5: Mobility trends for selected countries: Colombia vs. Western Europe, 2020



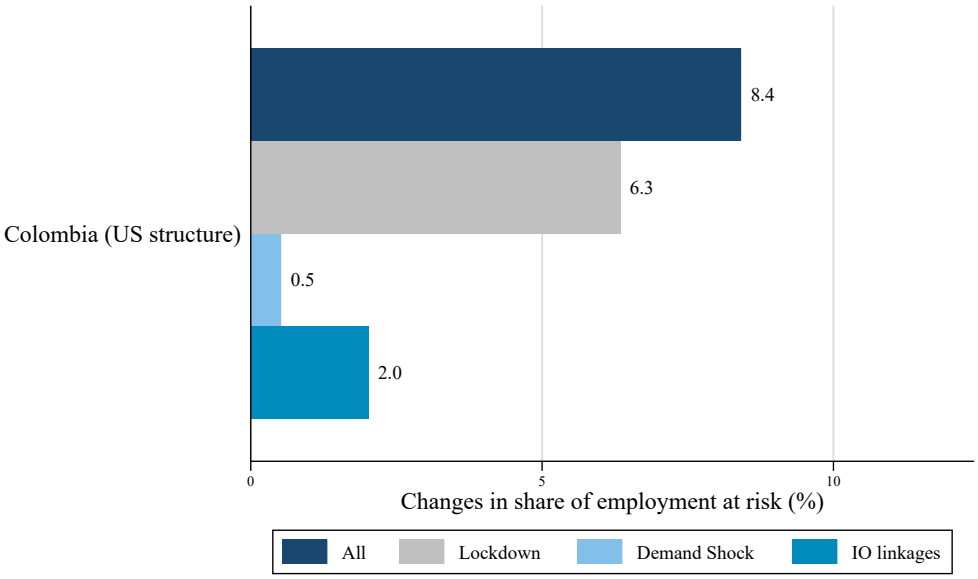
Note: The figure shows patterns in mobility as reported by Google Mobility. The baseline is the median value for the same day of the week between 3 January–6 February, 2020. Source: Google's COVID-19 Community Mobility Report.

Figure A6: Jobs at risk and value added at risk under a lockdown scenario with manufacturing and construction open: All shocks



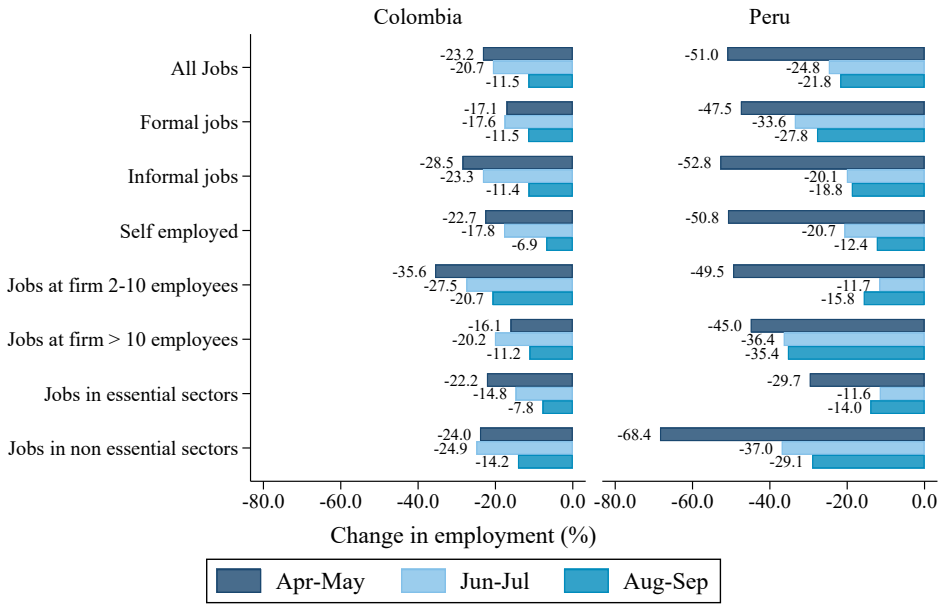
Note: This figure estimates jobs at risk and value added at risk under alternative scenarios of firm size and employment categories affected by the shock. The first set of bars in each graph represents a scenario in which informal jobs and those in micro firms (<10 employees) are affected. The middle set of bars adds jobs in small firms (10-50 employees). In the right-hand set, informal jobs are not affected or have already recovered. Bars labeled "U.S. structure" represent jobs at risk and value added at risk under the assumption that the distribution of workers is identical to that of the United States in terms of economic sectors, firm size and occupation.

Figure A7: Jobs at risk by source of shock under a lockdown scenario for US structure: All shocks



Note: This figure estimates jobs at risk by source of the shock. It refers to the simulation in which informal jobs and those in micro firms are affected (the left-hand set of bars in Figure 2). The impact of each source (lockdown, demand, IO linkages) is calculated as the difference in the jobs-at-risk measure that results from shutting down each source.

Figure A8: Strict employment losses by 2-month periods: Colombia and Peru, 2020 vs. 2019



This figure replicates Figure 4 taking into account all workers that report having a job, independent of whether they worked a positive number or hours

Table A.1: **Attributes of jobs for formal and informal workers (Shares,%)**

	Formal	Informal[1]
Self-Employed	16.1	65.5
At firms $\leq$ 10 employees	29.5	94.4
At firms 11-50 employees	15.2	3.5
Bottom labor income quartile	3.3	45.5
Second labor income quartile	24.7	26.9
Third labor income quartile	30.3	18.8
Top labor income quartile	41.6	8.8
Affiliated to contributory health care system	95.8	9.1
Has occupational safety and health	91.8	4.2
Has a contract	89.5	35.1
Has a verbal contract (if has contract)	5.2	89.0
Can telework	37.6	20.1
With labor income under minimum wage	8.0	69.7

[1]A worker is labeled as informal if their mandatory pension contributions are not paid. Source: Colombia Statistical Office (GEIH data).

Table A.2: Sector's weight in the economy, 2019
(Average for Argentina, Colombia and Peru)

ISIC Rev. 4 Section	Share of non essential workers (%)	Share of employ-ment (%)	Share of labor income (%)	Value Added / Labor Income
A. Agriculture; forestry and fishing	0	4.7	2.6	2.8
B. Mining and quarrying	100	0.7	1.8	5.2
C. Manufacturing	67	11.5	11.3	2.4
D. Electricity; gas, steam and air conditioning supply	0	0.3	0.5	6.1
E. Water supply; sewerage and waste management	0	0.5	0.5	4.0
F. Construction	100	8.0	7.5	2.8
G. Wholesale and retail trade; repair of motor vehicles	56	20.3	15.9	1.8
H. Transportation and storage	45	7.5	7.3	2.6
I. Accommodation and food service activities	100	7.0	4.6	1.8
J. Information and communication	6	1.6	2.4	2.5
K. Financial and insurance activities	0	1.6	3.2	2.4
L. Real estate activities	0	0.8	0.9	17.2
M. Professional, scientific and technical activities	0	3.4	5.5	1.8
N. Administrative and support service activities	24	4.0	3.6	1.4
O. Public administration; compulsory social security	0	5.5	9.7	1.1
P. Education	100	6.5	8.8	1.3
Q. Human health and social work activities	33	4.9	6.9	1.6
R. Arts, entertainment and recreation	100	1.6	1.4	2.0
S. Other service activities	45	4.2	2.8	2.1
T. Activities of households as employers	100	4.8	2.2	1.2

Source: Own calculations based on Argentina, Colombia, and Peru Statistical Offices (Household surveys and National Accounts data).

Table A.3: Characteristics of employment in the sector, 2019 (Shares, %)
(Average for Argentina, Colombia, and Peru)

ISIC Rev. 4 Section	Share of non essential workers	Informal	Self-Emp.	At Firm <10 Empl.[1]	At Firm 10-50 Empl.	Telework share
A. Agriculture; forestry and fishing	0	75	36	70	13	8
B. Mining and quarrying	100	25	9	18	14	23
C. Manufacturing	67	53	27	56	14	15
D. Electricity; gas, steam and air conditioning supply	0	13	3	7	7	38
E. Water supply; sewerage and waste management	0	48	33	45	8	17
F. Construction	100	73	30	72	12	8
G. Wholesale and retail trade; repair of motor vehicles	56	67	45	79	8	33
H. Transportation and storage	45	66	51	68	8	21
I. Accommodation and food service activities	100	74	29	77	14	14
J. Information and communication	6	31	20	37	15	65
K. Financial and insurance activities	0	15	7	17	13	67
L. Real estate activities	0	42	21	67	13	47
M. Professional, scientific and technical activities	0	34	43	72	13	72
N. Administrative and support service activities	24	45	31	45	13	27
O. Public administration; compulsory social security	0	14	10	13	7	54
P. Education	100	19	10	17	21	83
Q. Human health and social work activities	33	23	18	30	12	26
R. Arts, entertainment and recreation	100	62	34	60	17	35
S. Other service activities	45	77	63	86	6	21
T. Activities of households as employers	100	81	30	100	0	9

[1]Includes Self Employment. Source: Own calculations based on Argentina, Colombia, and Peru Statistical Offices (Household surveys data).

Table A.4: Characteristics of employment in the sector
(Average for Argentina, Colombia, and Peru).

ISIC Rev. 4 Section	Share of non essential workers	Demand Shock	IO Supply shock	IO Demand shock
A. Agriculture; forestry and fishing	0	0.0322	0.1825	0.0542
B. Mining and quarrying	100	0.0074	0.5788	-0.0065
C. Manufacturing	67	0.1092	0.4399	0.0568
D. Electricity; gas, steam and air conditioning supply	0	0.0243	0.4291	0.0409
E. Water supply; sewerage and waste management	0	0.0512	0.4314	0.0445
F. Construction	100	-0.0242	0.4403	0.0316
G. Wholesale and retail trade; repair of motor vehicles	56	0.0821	0.3363	0.0564
H. Transportation and storage	45	0.1278	0.4354	0.0309
I. Accommodation and food service activities	100	0.3386	0.1805	0.0379
J. Information and communication	6	0.0173	0.3725	0.0620
K. Financial and insurance activities	0	-0.0099	0.2662	0.0383
L. Real estate activities	0	-0.0622	0.1633	0.0242
M. Professional, scientific and technical activities	0	0.0616	0.4248	0.0601
N. Administrative and support service activities	24	0.0803	0.4289	0.0616
O. Public administration; compulsory social security	0	0.0126	0.1781	0.0236
P. Education	100	0.0278	0.0642	0.0092
Q. Human health and social work activities	33	0.0310	0.1211	0.0179
R. Arts, entertainment and recreation	100	0.1188	0.1770	0.0342
S. Other service activities	45	0.1188	0.2303	0.0338
T. Activities of households as employers	100	0.0000	0.0000	0.0000

Source: Own calculation based on Argentina, Colombia, and Peru Statistical Offices (Household surveys and National Accounts data).