IDB WORKING PAPER SERIES Nº IDB-WP-1150

The Unequal Impact of the Coronavirus Pandemic:

Evidence from Seventeen Developing Countries

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August 2020

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Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Bottan, Nicolas.
The unequal impact of the coronavirus pandemic: evidence from seventeen developing countries / Nicolas Bottan, Bridget Hoffmann, Diego A. Vera-Cossio.
p. cm. — (IDB Working Paper Series ; 1150)
Includes bibliographic references.
1. Coronavirus infections-Economic aspects-Latin America. 2. Coronavirus infections-Social aspects-Latin America. 3. Income distribution-Latin America. 4. Labor market-Latin America. 5. Unemployment-Latin America. 6. Small business-Latin America. 7. Food security-Latin America. I. Hoffmann, Bridget. II. Vera-Cossio, Diego A. III. Inter-American Development Bank. Department of Research and Chief Economist. IV. Title. V. Series.
IDB-WP-1150

http://www.iadb.org

Abstract

The current coronavirus pandemic is an unprecedented public health challenge that has devastating economic impacts for households. Using a sample of 230,540 respondents to online surveys in 17 countries in Latin America and the Caribbean, we show that the economic impacts are large and unequal: 45% of respondents report that a household member lost a job, and among households owning small businesses, 59% of respondents report that a household member closed their business. Among households with the lowest income prior to the pandemic, 71% report that a household member lost their job and 61% report that a household member closed their business. Declines in food security and healthiness are among the disproportionate impacts. Our results provide evidence that the current public health crisis will exacerbate economic inequality, and they are among the first estimates of the labor market and well-being impacts of the pandemic in developing countries[1].

JEL Codes: I14,D14,I18,I32

KEYWORDS

Coronavirus pandemic, Public health, Labor markets, Inequality

[1] We would like to thank Sebastián Espinoza and María Paula Medina for superb research assistance. We would like to thank Julián Cristia for his encouragement and advise with the project. We also want to thank Tom Sarrazin, Sebastián Oliva and Pablo Bachelet for their tremendous support in the dissemination of the survey. We also want to thank the support of IDB's country offices, country representatives and country economists for their invaluable input in customizing the questionnaires for each country. In particular, we want to thank Marta Ruiz Aranz and Diether Beuermann for their support in the rollout of the surveys in Central America and the Caribbean. We would like to thank Ana María Ibáñez, Eric Parrado, Michael Lovenheim, and the team of researchers in IDB's Research Department for valuable support and feedback in different parts of the project. Opinions, findings, conclusions and recommendations expressed here are those of the author and do not necessarily reflect the views of the Inter-American Development Bank.

1 | AUTHOR SUMMARY

Using a household survey of 230,540 respondents in 17 developing countries, we document the devastating labor market impacts of the coronavirus pandemic. We find that the relationship between job loss and business closure is monotonically decreasing with income prior to the pandemic, exacerbating existing inequality. These unequal labor market impacts lead to unequal impacts beyond income, including food security and nutrition. Cross-country comparisons suggest that the impacts of the pandemic are stronger in countries with higher rates of informality. Not only are households from high-informality countries losing their livelihoods at higher rates, but they are also less resilient to those negative shocks. We provide some evidence suggesting that differences in the strength of lockdown policies across countries and the ability to work from home can be related to these impacts. Furthermore, labor market impacts affect policy preferences, as support for policies to contain the coronavirus is weaker among those experiencing job loss or business closure. Our results are among the first and only estimates of the economic impacts of the coronavirus pandemic on households outside of developed nations, and we find impacts that are larger than those reported in developed countries.

2 | INTRODUCTION

Several prominent economists have posited that inequality is the principal economic issue of our era [1, 2, 3, 4]. Recent economic slowdowns, such as the Great Recession of 2008-2009, increased economic inequality [5, 6, 7]. However, compared to other economic downturns, the COVID-19 pandemic alters economic activity through different channels and on an accelerated timeline.

To slow the spread of COVID-19, governments have implemented regulations that require social distancing, close non-essential businesses, restrict travel, and in many cases require residents to remain in their homes [8]. The human interactions that drive the economy, such as working together in enclosed areas and enjoying entertainment activities, have been discouraged, restricted, or banned. Residents are complying with these measures, report strong support for these regulations [9, 10, 11], and actively seek out information [12]. Although these measures are necessary for public health, recent evidence from developed countries suggests that they have negative economic impacts in the short run [13, 14], and that they can potentially deepen pre-existing gaps [15]. These impacts could be exacerbated in developing countries with more vulnerable workers and firms, as well as lower levels of state capacity to face the pandemic.

Using a large-scale online household survey, we show that the COVID-19 pandemic has unequal economic impacts on households in Latin America and the Caribbean that will further exacerbate inequality. Research on economic inequality is particularly relevant in Latin America and the Caribbean. Although inequality and poverty declined over the past decade [16, 17], prior to the pandemic, the region still had the highest income inequality in the world [18], and a large share of citizens were vulnerable to falling back into poverty due to economic shocks [19].

3 | DATA COLLECTION AND VALIDATION

We conducted online surveys of households in eight South American countries (Chile, Colombia, Bolivia, Ecuador, Guyana, Peru, Suriname, and Uruguay), four North and Central American countries (Costa Rica, El Salvador, Mexico, and Panama), and five Caribbean countries (Dominican Republic, Bahamas, Barbados, Jamaica, and Trinidad and Tobago), resulting in a sample of 230,540 observations. The survey was first launched on March 27, 2020 and was launched in all countries in our sample by April 17, 2020. With the exception of Costa Rica, data collection continued until April 30, 2020. Therefore, the majority of the data were collected during the last two weeks of April 2020. The number of observations by country ranges from 565 to 35,556 (see Table S1 in the Supplementary Material section for country-specific details).

Figure S1 in the Supplementary Material section depicts the geographic coverage of our sample, showing the number of observations as a share of population (in %) by sub-national region for each country in our sample. Our sample achieved broad geographic coverage with observations in 92% of the sub-national regions and in 61% of the localities of countries in our sample (see Table S1).

We recruited participants 18 years old and over for the survey using paid advertisement posts on Facebook and Instagram. We used keywords with broad appeal, such as fútbol (soccer) or names of local celebrities, to avoid selecting participants based on COVID-19 knowledge or interest. The Supplementary Material section contains additional information about the social media campaigns and shows the posts that were used for Uruguay.

The questionnaire was largely standardized across countries to allow pooling the data across countries. The primary objective of the surveys was to measure the negative economic and well-being impacts of the current pandemic on households in Latin America and the Caribbean. For this reason, the questionnaire focused on collecting data on labor market outcomes, financial situation, and social program enrollment. In addition, the survey collected information on hunger, shortages of key goods, and agreement with different policies to slow the spread of COVID-19. A copy of the questionnaire can be found in the Supplementary Material section.

3.1 | Data Validation

To validate our dataset, we compare demographic characteristics using data from the online and nationally representative household surveys, collected through field visits. Columns (1) and (2) in Table S3 show that although the respondents of the online surveys are more educated and more likely to be female, they do not differ substantially in terms of household structure and income levels. Second, Columns (3) and (4) conduct an out-of-sample validation exercise and show that by re-weighting the online responses by the inverse probability of being in the nationally representative sample, the differences in demographic characteristics vanish. The Supplementary Material describes the steps to estimate weights for the online survey and the validation exercise.

In most of our analysis, we re-weight observations in our sample to achieve national representativeness (see Supplementary Material). These estimates also weight observations according to country population to account for differences in sample size across countries. The exception is Figure 3, which re-weights observations to account for temporal changes in the sample. See Supplementary Material for estimation details. All results are robust to not using weights at all, as shown in Figures S2-S4 and Table S4 in the Supplementary Material.

4 | RESULTS

We document that the COVID-19 pandemic has negative economic impacts for a broad segment of the population and that these impacts are magnified for those with lower income prior to the pandemic. Overall, 45% of respondents report that a household member lost a job and, among households owning small family businesses, 58% of respondents reported that a household member closed their business. The recall period for these questions was randomized between 1 week, 2 weeks, and 1 month. We find that the job-loss rates range between 42% for a recall period of one week to 47% for a recall period of a month. We also find that the rates of business closures remain constant at

58% across recall periods. Compared to similar statistics in the United States (43% in the case of small businesses [14]), we find greater rates of business closure, implying that the economic impacts of the pandemic may be stronger in developing countries.

These overall effects obscure highly unequal impacts across income levels prior to the pandemic. After accounting for fixed factors by country, the percentage of households reporting job losses declines monotonically with income in January 2020, prior to the onset of the pandemic (Figure 1). In the case of business closures, the decline is similar though less dramatic. Households reporting income of less than the national monthly minimum wage for January 2020 experienced the largest impacts, with nearly 71% reporting that a household member lost their job and 61% reporting that a household member closed their business. This contrasts sharply with the impacts reported by respondents with the highest household incomes. Among the highest income respondents, only 14% reported that a household member lost their job, and 54% reported that a household member closed their business.

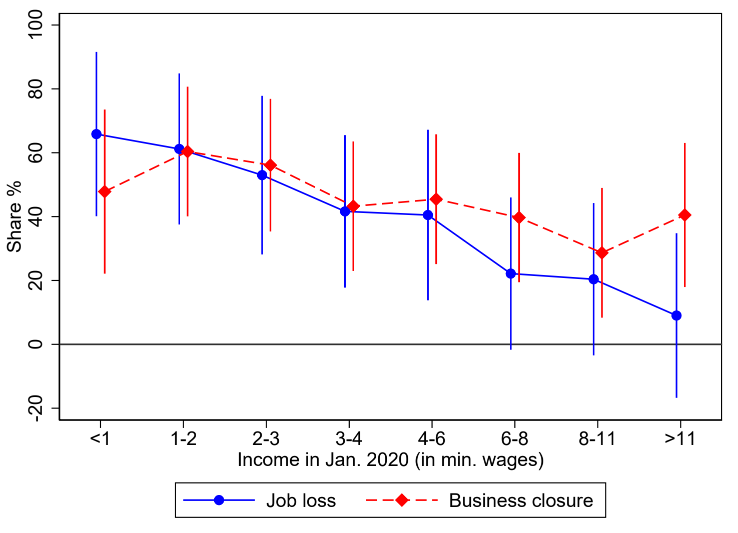

FIGURE 1 **Higher rates of job loss and business closure among households in the lowest income group.** Point estimates and 95% confidence intervals for regressing outcome on income bin indicators and country fixed effects. Data are weighted using within- and cross-country weights. See Empirical Methods in Supplementary Material for details.

One explanation for these patterns is that high levels of informality in the region may limit the ability of the most-vulnerable households to keep their sources of income. Using the share of self-employed workers as a proxy for the share of informal workers in the labor market, Figure 2 shows that labor market informality is positively correlated with loss of livelihood. Since informality rates are high in most developing countries, this result provides a novel explanation of why labor markets in developing countries are particularly hard-hit during the crisis.

Our data suggest two important explanations for the higher vulnerability of households in developing countries with high levels of informality. First, the type of policies to prevent the spread of the virus affects informal workers more. Our survey captures data from countries without enforced mobility-restriction policies or curfews such as Uruguay, but also more-stringent policies such as mandatory quarantines and closures of non-essential businesses, as in the case of Bolivia or Peru. As most informal and self-employed workers tend to work in jobs that are prone to contact with other people, such as those in the retail or services sectors, as opposed to office or industry jobs, the

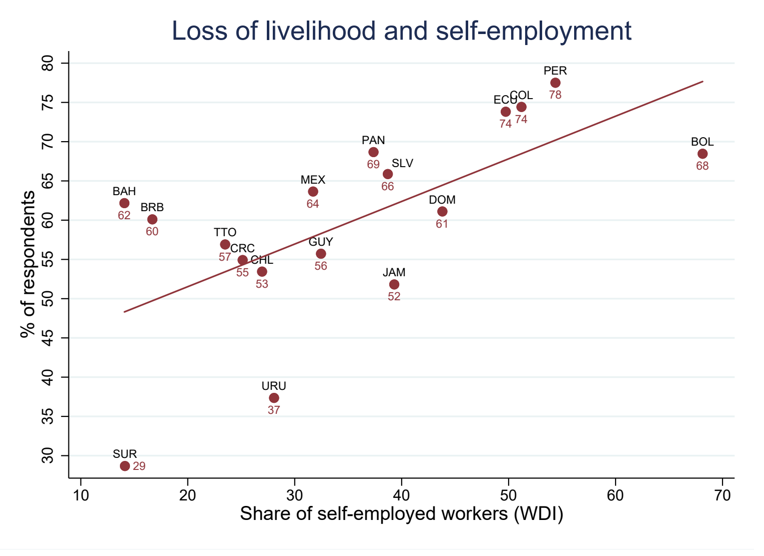

FIGURE 2 **Higher rates of livelihood loss in countries with higher informality.** Each dot represents the share of respondents who report that a household member lost a job or closed a business. Data are weighted using within- and cross-country weights.

latter set of policies may lead to larger disruptions in labor markets. Indeed, our sample indicates that the share of respondents reporting job losses in their household during April (69%) is substantially higher in countries with national or local mandatory quarantines, relative to those of countries that did not implement mobility-restriction measures (34%) or only implemented curfews (54%). See Supplementary Material section for a list of countries by type of policy.

Second, differences in the ability to telework could also be one reason that the negative impacts of the pandemic are concentrated among households with lower incomes. Among respondents that are still employed, we find that the share of respondents that report working from home during the past week is monotonically increasing with household income in January 2020. Thirty percent of workers from households with incomes below the national minimum wage reported working from home, while 76% of workers from the highest-income households report working from home.

Impacts on job loss and business closure translate into reductions in income. Table 1 reports within-locality changes in outcomes as a response to job loss or business closure. Column 1 of Panel A shows that respondents who reported a job loss or business closure are 24 percentage points (p-value<0.01) more likely to report a reduction in income. Overall, 71% of respondents report that they expect their household income in April 2020 to be lower than their household income in January 2020. Thirty-one percent of respondents reported household income less than the national monthly minimum wage for January 2020, and 56% of households report that they expect their household income to be less than the national minimum wage in April 2020. Figure 3 shows that the distribution of household income expected in April 2020 is a leftward shift of the distribution of household income in January 2020. In particular, the share of households with incomes marginally above the national minimum wage declines between January and April 2020, suggesting that many vulnerable households expect to fall into poverty.

We find that job loss and business closure lead to reductions in health and food security. Columns 2-3 of Panel A of Table 1 show that households with a job loss or business closure are 12 percentage points (p-value<0.01) more likely to suffer from hunger and 8 percentage points (p-value<0.01) more likely to have a less healthy diet relative to their

TABLE 1 The loss of livelihood during the pandemic is linked to changes in nutrition and policy support

Panel A: Impacts on income, food security, and health

	(1)	(2)	(3)
	Decreased income	Went hungry	Eats less healthy
Lost job or closed business	0.241***	0.127***	0.085***
	(0.008)	(0.008)	(0.008)
Observations	186,058	198,190	173,956
Adjusted R2	0.487	0.602	0.430

Panel B: Impacts on transfers and policy support

	(1)	(2)	(3)
	Gift/Loan	Gov. Priority	Lockdown (>=month)
Lost job or closed business	0.225***	-0.027***	-0.042***
	(0.008)	(0.008)	(0.010)
Observations	198,017	196,076	125,359
Adjusted R2	0.479	0.482	0.540
$*p < 0.1, **p < 0.05, ***p < 0.01$			

The table reports regression coefficients capturing the relationship between livelihood losses during the pandemic and outcomes. Each column reports the results of a regression of the dependent variable on an indicator of whether any household member either lost a job or closed a business and a vector of covariates. In addition, all regressions control for locality $\times$ day of survey completion fixed effects (18,764), as well as economic-sector fixed effects. Standard errors are clustered at the locality level (3,165). Data are weighted using within- and cross-country weights. See Empirical Methods in Supplementary Material section for details.

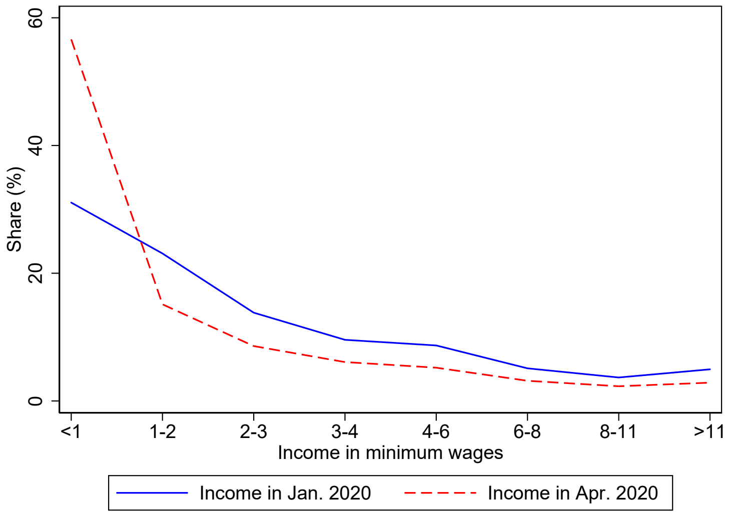

FIGURE 3 **The share of households in the bottom part of the income distribution is expected to increase.** Shares of households in each income bin for incomes reported for January 2020 and April 2020. Data counts weighted using within- and cross-country weights. See Empirical Methods in Supplementary Material for details.

diet prior to the pandemic. The results suggest that the impacts of the pandemic may have long-lasting consequences linked to declines in the stock of human capital. Consistent with the results from Figure 2, we also find that the consequences of the loss of livelihoods on food security are stronger in countries with higher levels of informality (See Table S5). This suggests that the structure of labor markets not only magnified the exposure to job losses and business closures, but also magnified the impacts of the loss of livelihoods on household welfare as informal workers may have lower access to formal safety nets.

We find that households cooperate across income levels to smooth the negative economic impacts of the pandemic. Seventy percent of respondents who reported January 2020 household income less than the national minimum wage reported that a household member received a gift or loan from a friend or relative. In contrast, only 26% of respondents with the highest incomes in January 2020 report that a household member received a gift or loan from a friend or relative. This pattern reverses for providing a gift or loan. Thirty percent of households with January 2020 income less than the national minimum wage reported that a household member provided a gift or loan compared to 57% of households with the highest incomes January 2020. Across all income categories, the reception of a gift or transfer is concentrated among households that reported losing a job or closing a business. Column 1 of Panel B of Table 1 shows that households that lost their livelihoods during the crises are 22 percentage points (p-value<0.01) more likely to receive transfers from relatives or friends. This highlights the importance of informal social protection networks as a tool to cope with the negative impacts of the pandemic.

Despite these substantial economic impacts, there is strong support for measures to slow the spread of the coronavirus. Overall, 77% of respondents agree with a statement that the top priority of the national government should be to stop the pandemic, and 54% of respondents think that non-essential businesses should be closed for one more month. Although support for these policies is broad, it is likely to decrease as more households lose their livelihoods. Column 2 of Panel B from Table 1 shows that the probability of agreeing with the idea that the Government's priority

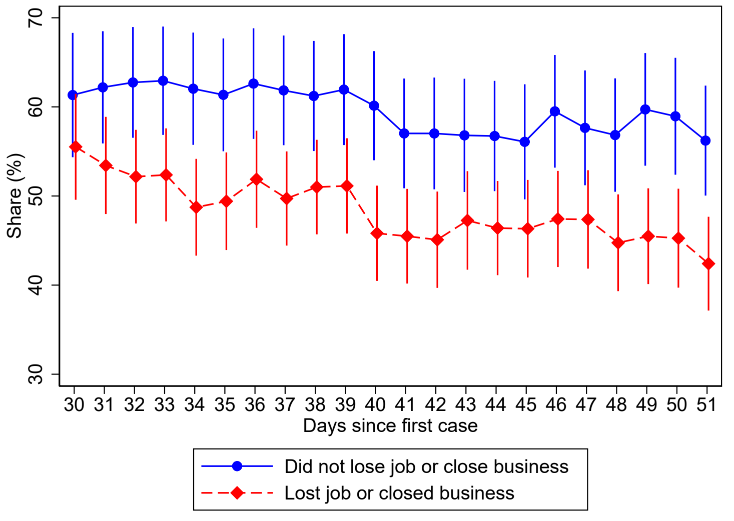

FIGURE 4 Support for extending lockdown policies declines more among households that lost their livelihoods. Point estimates and 95% confidence intervals for the share of respondents supporting extending lockdown policies according to days since first COVID-19 case in the country. Data are weighted using within- and cross-country weights. See Empirical Methods in Supplementary Material section for details.

should be fighting the pandemic is 2 percentage points (p-value$<$0.01) lower among households that experienced a job loss or business closure. Column 3 of Panel B shows that the loss of livelihoods during the pandemic is linked to a 4 percentage-point decline (p-value$<$0.01) in the probability of agreeing with closing non-essential business for one more month. Thus, the support for policies to slow the spread of the coronavirus is fragile. Indeed, Fig. 4 shows that, as days go by, the decline in support for keeping businesses closed for one more month declines faster among households that lose their livelihoods. One important implication is that, without further assistance to impacted households, compliance with mobility restriction policies is likely to decline.

5 | DATA ANALYSIS

| Figure 1

In Figure 1 we show how job loss and business closures vary throughout the income distribution. Job loss is a dummy variable that equals one if the respondent indicates that they lost their job within the last week, two weeks or month (these horizons were randomly assigned). Similarly, the variable for business closures equals one if subjects report that their business was forced to close by the government or by lack of demand within the same randomly assigned time horizon.

To explore differences in job loss and business closure across the income distribution, we first aggregate responses at the country and income bracket level using within-country weights as described in the Supplementary Material section. We then regress by OLS the country averaged outcome on indicators for income bin and control for country fixed effects, weighting by country population. Because we only have 17 countries in our sample, using standard clustered standard errors would result in incorrect inference. Therefore, we follow Bertrand et al. [20] by aggregating the data at the country level by income category. Figure 1 shows the point estimates and 95% confidence intervals for each income bin average. As a robustness test, we show results for the raw pooled data, without applying weights, in Figure S2 in the Supplementary Material.

| Figure 2

We present a cross-country comparison of the shares of households who lost their livelihoods as a function of the share of self-employed workers in the economy. For this, we identified the respondents who reported that at least one household member lost their job during or had to close their businesses during the survey reference period, and we obtained shares using weights to correct for sampling issues (see Supplementary Material section). Data corresponding to the share of self-employed workers was obtained from the World Bank's World Development Indicators.

| Figure 3

We present the share of household income in each income bin for incomes reported by respondents corresponding to January 2020 and April 2020 in Fig. 3. We restrict the sample to responses collected from April 13 to May 1, 2020 to include all countries. Shares are calculated by re-weighting counts by within- and across-country weights as detailed in the Supplementary Material section Estimation of Weights. As a robustness test, we show the results for the raw pooled data without applying weights in Figure S3.

| Figure 4

Figure 4 shows the share of respondents who support extending the lockdown policies by at least one month over time since the first COVID-19 case in the country. One challenge to exploring how support changes over time is that the timing of responses varies between countries. Therefore, over time we have new countries entering the sample, and the change in sample composition could bias our results. We address this issue in two steps. First, we construct new weights and re-weight respondents after day 31 to match those responding at the beginning of the series (days 30 and 31) on observable demographic characteristics.

We estimated a model by fitting a logistic function (logit) and computed predicted probabilities of having responded to the survey on day 30 or 31 relative to first case. As explanatory variables we include demographic characteristics such as household size, age indicators for: presence of children or elderly, having gone hungry, woman, education primary or less, college education or higher, household income categories (<1, 1-2,2-3, 8-11,>11), and day of week. We then used inverse probability weights based on the propensity score obtained.

Second, we separately estimate OLS regressions for respondents whose household member lost job or closed business and for those who did not, where the dependent variable is an indicator variable that equals one if they support extending the lockdown by at least a month, and zero otherwise. The independent variables are indicators for days since first COVID-19 case, day of week indicators, and country fixed effects. The regression is weighted by the inverse probability weight described in step one and we employ robust standard errors. Figure 4 presents the point estimates and 95% confidence intervals for these estimates. We present similar estimates when using the pooled raw data without re-weighting in Figure S4 in the Supplementary Material.

| Table 1

In Table 1, we report comparisons of differences in the relevant outcomes among respondents whose households experienced a loss of livelihood during the pandemic period. To control for time-varying characteristics we perform comparisons focusing on respondents who are in the same locality and who completed the survey during the same day. We exploit granular data from over 3,000 localities in 17 countries. Thus, we focus our analysis on the subset of 18,000 locality-date-of-response cells that include more than one observation. This approach allows us to isolate time-varying locality shocks and thus purge regional confounding factors. In addition, we control for industry sector fixed effects to prevent differences in the sectors related to the household's main economic activities from driving the results, as exposure to the effects of the pandemic may vary across sectors.

We operationalize our approach by estimating the following specification, which is similar to that used in Gertler and Gruber [21]:

$$\mathrm{Y_{i,l,c,t}} = \beta \mathrm{Lostlivelihood_{i,l,c,t}} + \mathbf{X}_{i,c,l,t}\Sigma + \delta_{l,c,t} + \theta_s + \epsilon_{i,l,c,t} \tag{1}$$

Here, $Y_{i,l,c,t}$ denotes the outcome of interest corresponding to respondent i in locality l from country c collected in date t. Lost livelihood$_{i,l,c,t}$ is an indicator of whether any member of the respondent's household lost her/his job or closed her business during the past week, two weeks, or month. $\mathbf{X}_{i,c,l,t}$ is a vector of demographic characteristics of the respondent (age, education level and gender) and of household characteristics (household size, presence of children younger than 5, presence of school-age children, and people 60 years old or older). $\delta_{l,c,t}$ denotes locality-date fixed effects, and θ_s denotes industry fixed effects based on the main pre-pandemic source of income of the respondent's household. $\epsilon_{i,c,l,t}$ denotes unobserved shocks. To account for possible serial correlation of outcomes within localities, we cluster the standard errors at the locality-country level.

The parameter of interest, β, is reported in Table 1 and captures within-locality differences in outcomes between respondents whose households experienced a loss of livelihood during the pandemic and those who did not. The reported models are estimated using weights to achieve country-level representativeness, to correct for differences in sample size across countries, and to provide weights based on country population size. All results are robust to excluding these weights (see Robustness Section in Supplementary Material).

To investigate whether the correlates of job loss or business closures and household outcomes are stronger in countries with high levels of informality, we also estimate the following specification:

$$\begin{aligned}\mathrm{Y_{i,l,c,t}} = \quad & \beta_1 \mathrm{Lostlivelihood_{i,l,c,t}} + \beta_2 \mathrm{Lostlivelihood_{i,l,c,t}} \times \mathrm{Self-employment}_c \\ & + \mathbf{X}_{i,c,l,t}\Sigma + \delta_{l,c,t} + \theta_s + \epsilon_{i,l,c,t}\end{aligned} \tag{2}$$

where *Self-employment* denotes the share of self-employed workers in country c and was obtained from the World Bank's World Development Indicators, using the most-recent observations for each country. We also report results using the share of informal workers (as a share of non-agricultural workers) in each country. This information was not available for Suriname, Jamaica, Trinidad and Tobago, Barbados, and Bahamas. See results in Table S4 in the Supplementary Material.

Dependent variables: *Went hungry* is an indicator of whether any household member went hungry during the past week due to lack of food. *Eats less healthy* takes the value of one if the respondent somewhat or totally agrees with the statement "I eat more unhealthy foods than normal." *Gifts/Loans* is an indicator of whether the respondent's household received a gift or transfer from either friends or relatives during the preceding week. Gov. Priority is an indicator of whether the respondent somewhat agrees or totally agrees with the statement "The government's priority should be to stop the spread of the pandemic." *Lockdown (>= month)* is an indicator of whether the respondent reports agreeing with closing non-essential business for one month or longer. As this question was asked only of people who reported agreeing with policies that require non-essential businesses to close, $Lockdown(>= month)$ takes the value of zero when the respondent reported not supporting measures of keeping non-essential businesses closed at all, regardless of the time.

6 | ROBUSTNESS

We demonstrate that all our results are robust to not re-weighting observations. Reassuringly, all results are both qualitatively and quantitatively similar. See SI Appendix, Figures S2-S4 and Panel A of Table S4 in the Supplementary Material for unweighted results.

In addition, Panels B and C of Table S4 in the Supplementary Material report robustness related to using only country-date fixed effects instead of locality-date fixed effects as controls, both with and without weights. Reassuringly, our results are both quantitatively and qualitatively similar.

7 | CONCLUSIONS

These results show that the negative economic impacts of the COVID-19 pandemic have been concentrated among those with lower incomes prior to the pandemic. This finding is important from both social and economic perspectives. Inequality is an important social outcome in itself and also has important economic implications. Although further research is needed, several studies have found that current inequality is negatively correlated with future economic growth [22, 23], and in particular, inequality driven by the lower tail of the income distribution stunts economic growth [24]. This implies that the unequal economic impacts of this short-term public health pandemic could have long-term implications for economic growth. In addition, our results indicate that country-level rates of informality in labor markets are linked to stronger negative impacts and low resilience, suggesting that prompt policy responses are needed to protect informal workers.

8 | SUPPLEMENTARY MATERIAL

Figure S1

Sample has broad geographic coverage at the sub-national level. The sub-national regions of each country in the sample are shaded according to number of observations as a share of population (in %). Sources of population data for each country are shown in the Supplementary Material Section.

Figure S2

Higher rates of job loss and business closure among households in the lowest income group. Point estimates and 95% confidence intervals for regressing outcome on income bin indicators and country fixed effects. Pooled data (no weights), robust standard errors. See the Empirical Methods section in the main text for more details.

Figure S3

The share of households in the bottom part of the income distribution is expected to increase. Shares of households in each income bin for incomes reported for January 2020 and April 2020. Pooled data (no weights). See the Empirical Methods section in the main text for more details.

Figure S4

Support for extending lockdown policies declines more among households that lost their livelihoods. Point estimates and 95% confidence intervals for the share of respondents supporting extending lockdown policies according to days since first COVID-19 case in the country. Pooled data (no weights). See the Empirical Methods section in the main text for more details.

Table S1

Date of Launch and Number of Observations by Country.

Table S2

Parameters of logit models for the probability of being in the nationally representative survey.

Table S3

Differences between Online Survey Data and Household (field) Survey Data.

Table S4

Loss of livelihoods and changes in well-being, and policy support (unweighted results).

Table S5

Impacts of livelihood loss on income and food security by labor-market characteristics.

Supplementary Information

| Data Collection and Construction

| Questionnaire

The questionnaire asks about monthly total household income in January 2020 and expected monthly total household income in April 2020 in ranges constructed as multiples of the minimum wage. The questionnaire asked if total household income was reduced during the past week. The questionnaire asked whether a household member lost their job or closed their business. The recall period for these questions was randomized between 1 week, 2 weeks, and 1 month. For respondents who remain in the labor market, the questionnaire asks whether the respondent worked outside the home or from home during the past week, and we code a variable to represent teleworking if the respondent reported working from home. Using the past week as the recall period, the questionnaire asks if any member of the household went hungry due to lack of food and asks respondents to report the strength of their agreement with a statement "I am eating less healthy than normal" on a scale from 1 (complete disagreement) to 5 (complete agreement). The questionnaire asks if any member of the household received (gave) a transfer or a loan from (to) another household during the past week. The questionnaire also asks respondents to report the strength of their agreement with a statement that COVID-19 should be the top priority of the national government on a scale from 1 (complete disagreement) to 5 (complete agreement) and asked whether respondents think that non-essential businesses should close.

Sample questionnaires in English, Spanish and Dutch can be downloaded here: https://www.dropbox.com/sh/uuv17cfaz94kw4h/AAAWvgJUNYEBHhNxZPcQVv3Za?dl=0.

| Data Construction

The questionnaire was implemented online using Qualtrics. Column (1) of Table S1 displays the launch date of the survey in each country. We construct the data set in several steps and the resulting number of observations that comprise the sample for each country is shown in column (2) of Table S1. First, we restrict the sample to completed surveys. Overall, approximately 59% of surveys that are started are completed. Second, we restrict the sample to surveys associated with IP addresses within the borders of the country for which the respondent is completing the survey. Across all countries in the sample, over 99% of completed surveys comply with this criteria. Third, Qualtrics flags surveys that are completed on the same device and likely to be repeat surveys completed by the same individual or household based on cookies. This is an imperfect filter. For example, it will not recognize repeated surveys by the same individual or household that are completed on different devices. Surveys flagged as repeats comprise less than 2.3% of completed surveys and we drop these surveys from the sample.

Recruitment Materials

Recruitment through Social Media Posts

We recruited participants for the survey using paid advertisement posts on Facebook and Instagram. To be eligible to participate in the survey, participants had to be at least 18 years old. In each country, we targeted the social media campaign to people ages 19 and up. We utilized keywords that have broad appeal in the country, such as futbol (soccer) and the names of futbol stars or local celebrities, and that are unrelated to COVID-19 in order to avoid selecting respondents based on their knowledge or experience regarding the current pandemic. In countries in which the average age of our sample was high or expected to be high, we utilized a second, simultaneous social media campaign with the same images and keywords, but specifically targeted to millennials aged 24-35.

In each country, we used three posts, an image of a male wearing a face mask, an image of a female wearing a face mask, and an image of an iconic landmark in that country. The posts were adapted to each country by changing the image of the landmark, changing the image of the male and female if appropriate, changing the country name in the text, and changing the language (Spanish, English, or Dutch) of the posts. Facebook algorithms select which post to show each user. As an example, we show the posts that we used for Uruguay below.

Re-weighting and external validity

Estimation of weights

For each country, we modeled the probability of being in the nationally representative sample as a function of demographic, time-invariant characteristics such as gender, age and education of the respondent, indicators for the presence of children of 5 years old or younger in the household and elderly (60 years old or older) in the households, as well as the number of household members and the number of children enrolled in school. Finally, we also include region-specific indicators.

We conducted this process country by country. For each country, we used the most recent nationally representative survey available in the Inter-American Development Bank harmonized survey data repository. We estimated the model by fitting a logistic function (logit) and computed predicted probabilities of being in the nationally representative data set ($\hat{p}_{i,c}$) for each respondent i in country c (see Table S2). We then used inverse probability weights ($ipw_{i,c} = 1/(1 - \hat{p}_{i,c})$) to, at least in terms of observable characteristics, resemble those from nationally representative surveys.

To prevent differences in response rates from driving the results, we re-scale the within-country weights $ipw_{i,c}$ by the inverse share of re-weighted number of responses per country, relative to the country's population size

$(Population_c/(\sum_i^{N_c} ipw_{i,c}))$.

Out-of-sample validation

We validate the country-specific weights by looking at their out-of-sample performance. For each country we randomly selected 60% of the observations in the online survey and the household (field) surveys. We used this sample to estimate logit models. We then use the resulting models to predict the probability of being observed in the household survey over the observations in the remaining 40% of the sample, which we call the testing sample. We then re-weight the observations in the testing sample and compare the adjusted means of demographic characteristics to those obtained from household (field) survey data. Table S3 shows this exercise in Columns 3 and 4. We were able to reduce the differences in respondent characteristics between the online and household surveys. This out-of-sample exercise suggests that the improvement in balance is not driven by overfitting. We also show that our online data do not differ substantially from the household survey data in non-targeted moments such as the proportion of respondents by income category.

Countries by type of mobility-restriction policies

The following list details the type of mobility restrictions implemented by each country. Data were collected from official government websites and press articles. The information was collected on April 23, 2020.

No mandatory policies: Bahamas, Suriname, Trinidad and Tobago, Uruguay. **Curfews:** Dominican Republic, Guyana. **Local Quarantines:** Chile, Jamaica, Mexico. **National Quarantines** Barbados, Bolivia, Colombia, Costa Rica, Ecuador, El Salvador, Panama, Peru.

Datasets

Population and Household Survey Data

Year and Source of Household Survey Data by Country

Country	Survey Name	Year	Link to source
Bahamas	LFS	2014	http://www.bahamas.gov.bs/wps/portal/public
Barbados	BSLC	2016	http://sistemasintegrales.cl/project/barbados-survey-of-living-conditions/
Bolivia	ECH	2018	https://www.ine.gob.bo/index.php/herramientas/bases-de-datos-catalogo-anda/bases-de-datos-encuestas-sociales/
Chile	Casen	2017	http://observatorio.ministeriodesarrollosocial.gob.cl/casen-multidimensional/casen/basedatos.php
Colombia	GEIH	2018	http://microdatos.dane.gov.co/index.php/catalog/659/get_microdata
Costa Rica	ENAHO	2018	https://www.inec.cr/noticias/enaho
Dominican Republic	ENCFT	2018	https://www.bancentral.gov.do/a/d/2539
Ecuador	ENEMDU	2018	https://www.ecuadorencifras.gob.ec/estadisticas/
El Salvador	EHPM	2018	http://www.digestyc.gob.sv/index.php/temas/des/ehpm.html
Guyana	LFS	2018	https://statisticsguyana.gov.gy/data/databases/
Jamaica	SLC	2014	https://statinja.gov.jm/living_conditions_poverty.aspx
Mexico	ENIGH	2018	https://www.inegi.org.mx/programas/enh
Panama	EHPM	2018	https://www.inec.gob.pa/publicaciones/Default2.aspx?ID_CATEGORIA=5&ID_SUBCATEGORIA=38
Peru	ENAHO	2018	https://webinei.inei.gob.pe/anda_inei/index.php/catalog/672
Suriname	SLC	2017	https://statistics-suriname.org/en/
Trinidad & Tobago	CSSP	2015	https://cso.gov.tt/methods/classifications/
Uruguay	ECH	2018	http://www.ine.gub.uy/encuesta-continua-de-hogares1

We used the most recent household survey available at the IDB's harmonized database repository. Each survey can be accessed on the websites of the specific institutions in each country. The table provides links to original sources for data access. In some instances, the microdata must be requested directly from the competent body due to privacy restrictions.

Year and Source of Population Data by Country

Country	Year	Link to Source
Bahamas	2010	https://www.bahamas.gov.bs/wps/wcm/connect/22f9b2b0-68fa-4a26-8bd8-474952e42dc2/Population+Projection+Report+2010-2040.pdf?MOD=AJPERES
Barbados	2010	https://web.archive.org/web/20170118220332/http://www.barstats.gov.bb/files/documents/PHC_2010_Census_Volume_1.pdf
Bolivia	2020	https://www.ine.gob.bo/subtemas_cuadros/demografia_html/PC20106.htm
Chile	2020	https://www.ine.cl/estadisticas/sociales/demografia-y-vitales/proyecciones-de-poblacion
Colombia	2020	https://www.dane.gov.co/index.php/estadisticas-por-tema/demografia-y-poblacion/proyecciones-de-poblacion
Costa Rica	2020	https://www.inec.cr/poblacion/estimaciones-y-proyecciones-de-poblacion
Dominican Republic	2020	https://www.one.gob.do/demograficas/proyecciones-de-poblacion
Ecuador	2020	https://sni.gob.ec/proyecciones-y-estudios-demograficos
El Salvador	2020	https://www.transparencia.gob.sv/search?utf8=%E2%9C%93&ft=Proyecciones+municipales
Guyana	2012	https://statisticsguyana.gov.gy/publications/#elementor-tab-content-1465%20%3E%20ul:nth-child(3)%20%3E%20li:nth-child(1)%20%3E%20span
Jamaica	2018	https://statinja.gov.jm/Demo_SocialStats/PopulationStats.aspx
Mexico	2020	https://www.gob.mx/cms/uploads/attachment/file/63977/Documento_Metodologico_Proyecciones_Mexico_2010_2050.pdf
Panama	2020	https://www.inec.gob.pa/publicaciones/Default3.aspx?ID_PUBLICACION=499&ID_CATEGORIA=3&ID_SUBCATEGORIA=10
Peru	2020	http://proyectos.inei.gob.pe/web/biblioineipub/bancopub/Est/Lib0846/libro.pdf
Suriname	2012	https://statistics-suriname.org/en/census-statistics-2012/
Trinidad and Tobago	2011	https://cso.gov.tt/census/2011-census-data/
Uruguay	2020	http://www.ine.gub.uy/estimaciones-y-proyecciones

Supplementary Figures

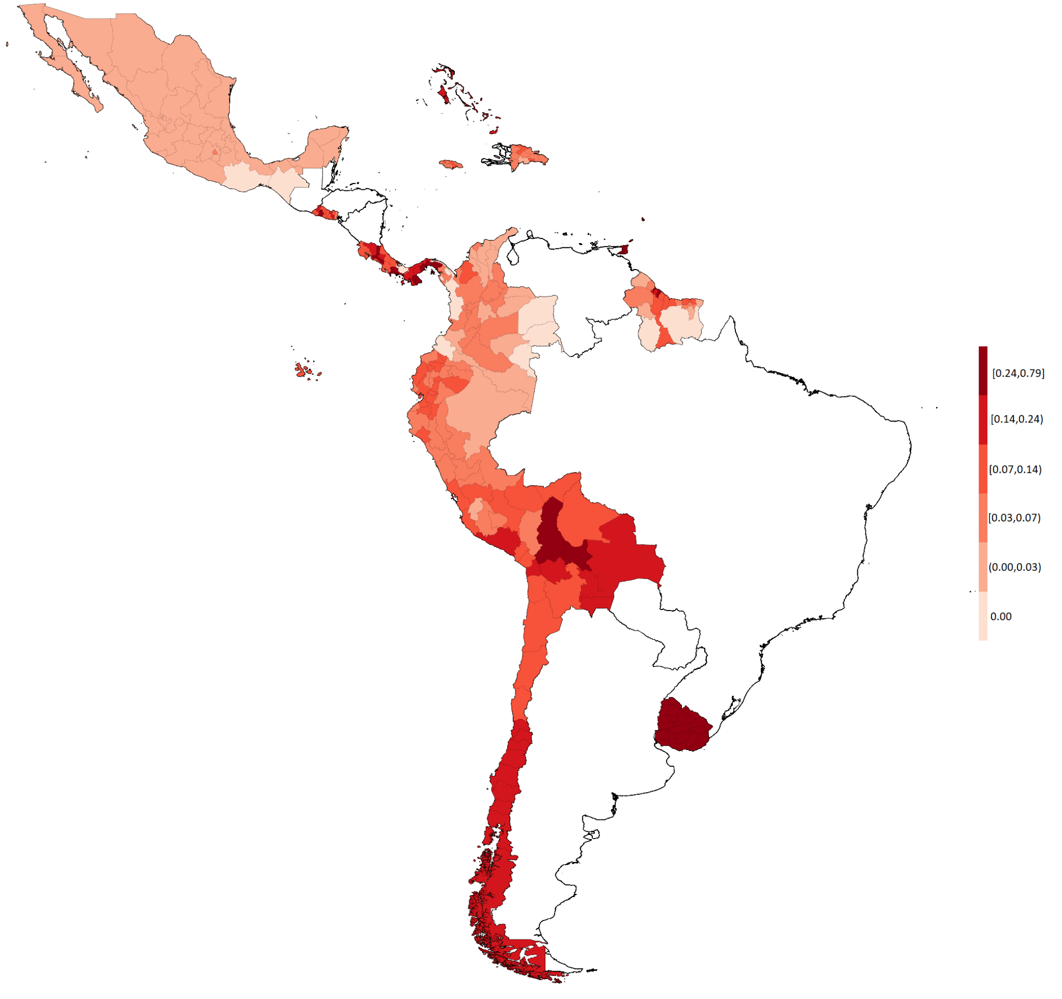

FIGURE S1 Sample has broad geographic coverage at the sub-national level. The sub-national regions of each country in the sample are shaded according to number of observations as a share of population (in %). Sources of population data for each country are shown in the Supplementary Text Information Section.

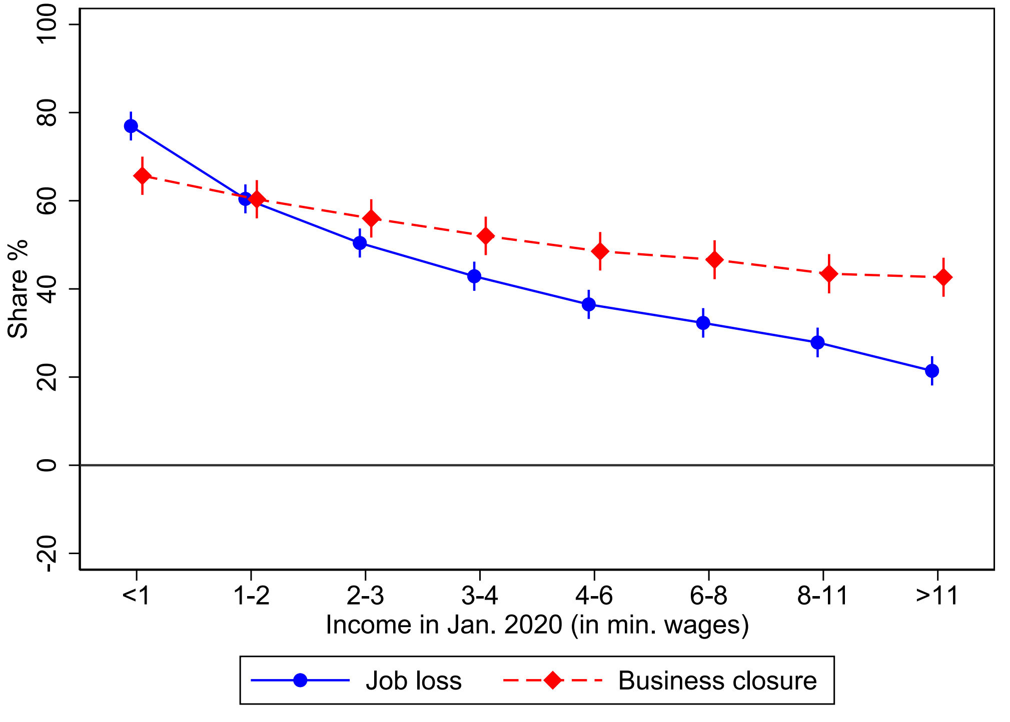

FIGURE S2 Higher rates of job loss and business closure among households in the lowest income group. Point estimates and 95% confidence intervals for regressing outcome on income bin indicators and country fixed effects. Pooled data (no weights), robust standard errors. See the Empirical Methods section in the main text for more details.

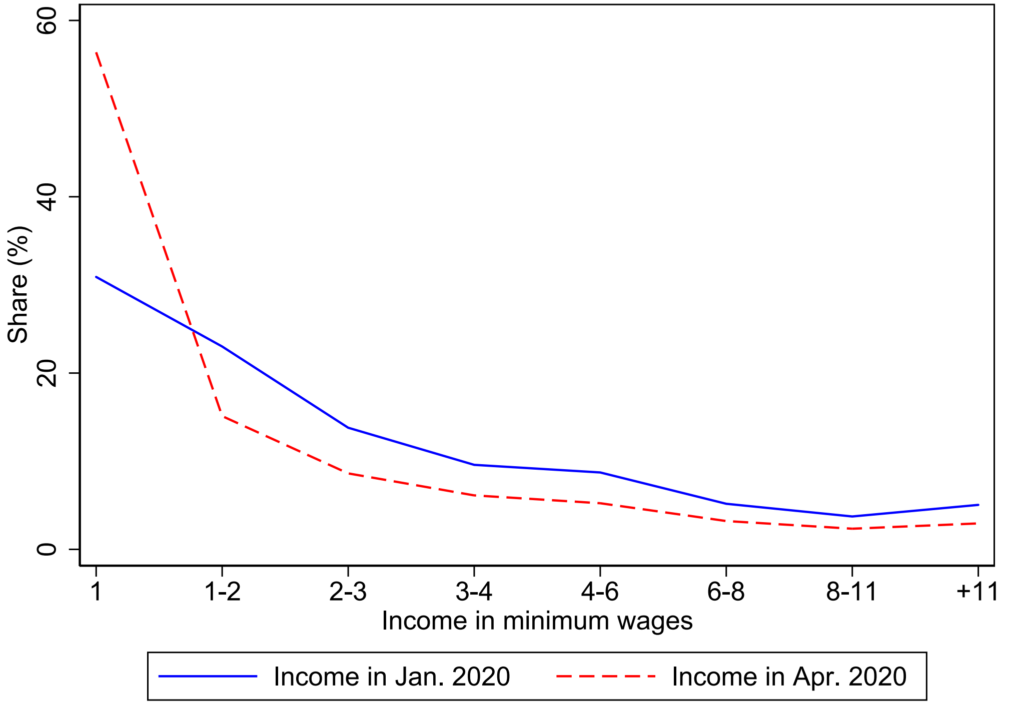

FIGURE S3 The share of households in the bottom part of the income distribution is expected to increase. Shares of households in each income bin for incomes reported for January 2020 and April 2020. Pooled data (no weights). See the Empirical Methods section in the main text for more details.

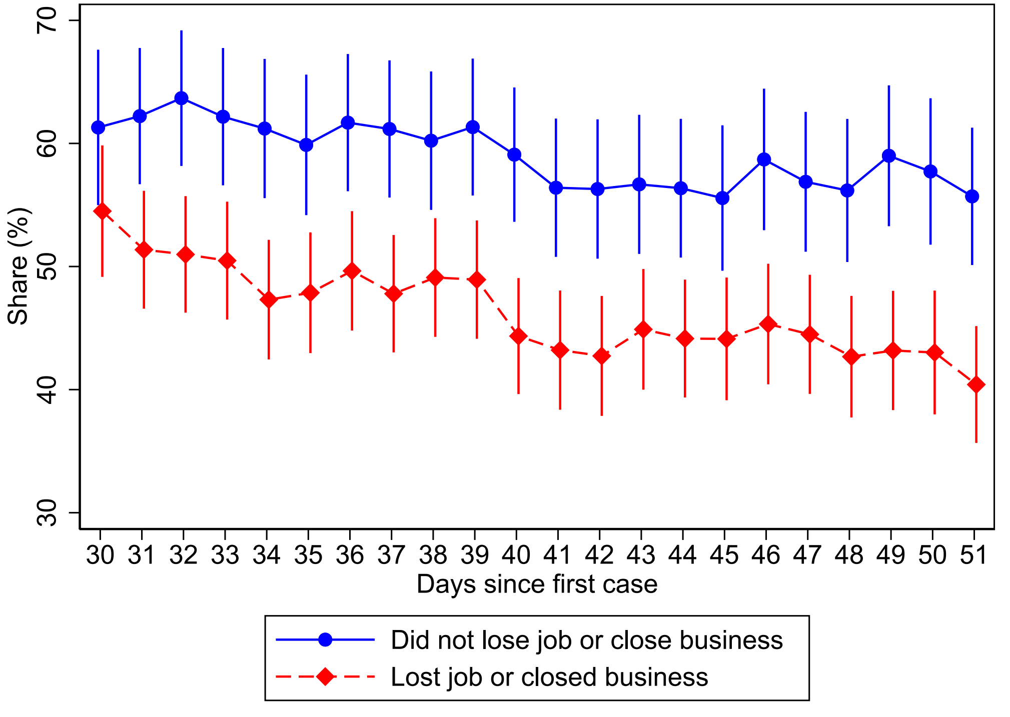

FIGURE S4 Support for extending lockdown policies declines more among households that lost their livelihoods. Point estimates and 95% confidence intervals for the share of respondents supporting extending lockdown policies according to days since first COVID-19 case in the country. Pooled data (no weights). See the Empirical Methods section in the main text for more details.

Supplementary Tables

TABLE S1 Date of Launch and Number of Observations by Country

Country	(1) Launch Date	(2) No. of Observations	(3) % of Localities with Observations
Chile	3/27/2020	35,556	97%
Bolivia	4/1/2020	25,970	83%
Panama	4/3/2020	15,521	100%
Uruguay	4/3/2020	21,191	64%
Peru	4/7/2020	25,452	47%
Mexico	4/13/2020	19,483	51%
Costa Rica	4/13/2020	9,151	90%
Colombia	4/15/2020	23,458	71%
El Salvador	4/16/2020	13,456	50%
Dominican Republic	4/16/2020	7,965	94%
Barbados	4/16/2020	2,072	100%
Jamaica	4/16/2020	2,547	91%
Guyana	4/16/2020	1,670	96%
Bahamas	4/16/2020	896	81%
Trinidad and Tobago	4/16/2020	4,683	100%
Ecuador	4/16/2020	18,688	68%
Suriname	4/17/2020	565	100%

Date of launch is the date on which the social media posts began. The date that the survey was rolled out in each country was largely determined by bureaucratic processes and approvals. With the except of Costa Rica, data collection in each country continued until April 30, 2020. The number of observations for each country reflected the number in the sample after data cleaning. The percent of localities is the percent of localities of each country for which we have one or more observations in the sample.

TABLE S2 Parameters of logit models for the probability of being in the nationally representative survey

	Bahamas	Barbados	Bolivia	Chile	Colombia	Costa Rica	Dominican Rep.	Ecuador	El Salvador	Guyana	Jamaica	Mexico	Peru	Panama	Suriname	Trinidad & Tobago	Uruguay
Household size	-0.002	-0.575***	-0.206***		-0.123***	-0.073***	-0.061***	-0.084***	-0.047***	-0.195***	-0.326***	-0.048***	-0.085***	-0.097***	-0.197***	-0.067***	-0.125***
	(0.034)	(0.020)	(0.008)		(0.007)	(0.013)	(0.020)	(0.009)	(0.012)	(0.031)	(0.044)	(0.008)	(0.006)	(0.011)	(0.032)	(0.009)	(0.009)
# of children in school age	-0.814***		0.389***	0.225***	0.168***	0.124	0.138**	0.563***	0.153*	0.973***	2.720***	0.583***	0.967***	0.080			0.665***
	(0.135)		(0.033)	(0.008)	(0.040)	(0.096)	(0.066)	(0.027)	(0.089)	(0.108)	(0.201)	(0.039)	(0.033)	(0.059)			(0.051)
Children under 5 years old in household (%)	-0.238**		-0.455***		-0.348***	-0.264***	-0.257***	-0.835***	-0.299***	-0.891***	-3.600***	-0.689***	-1.104***	-0.097*			-0.701***
	(0.112)		(0.030)		(0.037)	(0.093)	(0.061)	(0.023)	(0.087)	(0.082)	(0.203)	(0.035)	(0.030)	(0.056)			(0.047)
Elderly in household (%)	-0.520***	0.702***	-1.010***	0.038**	-0.167***	0.073*	-0.329***	-0.072**	-0.183***	-0.013	0.157	-0.103***	-0.280***	0.028	0.138	0.066	0.183***
	(0.133)	(0.066)	(0.030)	(0.016)	(0.024)	(0.040)	(0.058)	(0.032)	(0.037)	(0.110)	(0.155)	(0.025)	(0.022)	(0.039)	(0.177)	(0.041)	(0.026)
# of children enrolled in school	-0.831***	-1.060***	-0.325***	-1.366***	-0.737***	-0.699***	-0.460***	-0.360***	-0.234***	-0.964***	-1.879***	-0.564***	-0.645***	-0.338***	-0.588***	-1.100***	-0.983***
	(0.122)	(0.065)	(0.027)	(0.016)	(0.021)	(0.033)	(0.048)	(0.028)	(0.032)	(0.100)	(0.168)	(0.021)	(0.019)	(0.034)	(0.166)	(0.040)	(0.022)
Respondent is a female	-0.071	0.000	-1.108***	-2.543***	-2.018***	-2.227***	-0.996***	-3.228***	-2.272***	-1.208**	1.027*	-1.843***	-1.773***	-2.076***	-1.642		-1.671***
	(1.122)	(.)	(0.186)	(0.127)	(0.182)	(0.197)	(0.264)	(0.149)	(0.143)	(0.532)	(0.580)	(0.167)	(0.192)	(0.587)	(1.061)		(0.191)
Completed Primary	-2.205**	0.110	-3.632***	-4.496***	-3.329***	-3.297***	-3.660***	-3.478***	-3.874***	-4.066***	-1.585***	-5.006***	-4.477***	-4.905***	-5.261***		-4.638***
	(1.029)	(0.349)	(0.167)	(0.126)	(0.178)	(0.197)	(0.218)	(0.145)	(0.141)	(0.505)	(0.545)	(0.163)	(0.180)	(0.580)	(1.018)		(0.190)
Completed Secondary	-5.185***	-1.623***	-6.316***	-6.035***	-5.904***	-5.698***	-6.427***	-6.900***	-6.614***	-6.726***	0.000	-6.797***	-6.041***	-8.058***	-10.927***		-5.377***
	(1.021)	(0.346)	(0.165)	(0.125)	(0.176)	(0.196)	(0.217)	(0.143)	(0.139)	(0.508)	(.)	(0.162)	(0.180)	(0.580)	(1.070)		(0.190)
University/Vocational Training or Higher	0.010**	-0.010***	0.039***	-0.017***	0.004***	0.011***	0.016***	0.007***	0.006***	0.009***	0.018***	-0.017***	0.015***	0.019***	-0.003	0.017***	0.002***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.005)	(0.001)	(0.001)	(0.001)	(0.006)	(0.001)	(0.001)
Age of respondent			-0.385***		-0.181***	-0.398***	-0.452***	-0.611***	-0.500***	0.044	0.214	-0.221***	-0.282***	-0.082*		-0.011	-0.065**
			(0.032)		(0.026)	(0.045)	(0.055)	(0.034)	(0.040)	(0.113)	(0.151)	(0.027)	(0.023)	(0.044)		(0.048)	(0.029)
N	6413	11314	48150	201380	159692	34367	19722	58403	61294	10323	13363	199884	115388	41597	5376	29008	103015

$*p < 0.1, **p < 0.05, ***p < 0.01$

The table presents estimates of coefficients from a logit model of the probability of being the nationally representative household survey as a function of demographic characteristics. The models were estimated separately for each country. All models also included region-specific indicators, except in the case of Ecuador,in which data regarding regions were not available. Empty cells in the table imply that the relevant variable was not available in the household surveys. Robust standard errors are presented in parenthesis.

TABLE S3 Differences between Online Survey Data and Household (field) Survey Data

	Full Sample		Testing sample	
	(1)	(2)	(3)	(4)
	Online	HH Survey	Online	HH Survey
	(Raw)	(Sampling weights)	(Re-weighted)	(Sampling weights)
Household size	4.27	3.87	4.30	3.87
Children under 5 years old in household (%)	0.28	0.24	0.33	0.24
Elderly in household (%)	0.35	0.36	0.36	0.36
# of children enrolled in school	1.04	0.81	0.89	0.81
Respondent is a female	0.70	0.52	0.58	0.52
Completed Primary	0.03	0.36	0.31	0.36
Completed Secondary	0.22	0.32	0.30	0.32
University/Vocational Training or Higher	0.74	0.12	0.24	0.12
Age of respondent	38.13	43.07	39.62	43.04
Income categories				
0-0.5 MW	0.10	0.14	0.17	0.14
0.5-1 MW	0.16	0.09	0.22	0.09
1-2 MW	0.21	0.20	0.22	0.20
2-3 MW	0.14	0.15	0.11	0.16
3-4 MW	0.11	0.10	0.08	0.10
4-6 MW	0.10	0.12	0.07	0.12
6-8 MW	0.06	0.06	0.04	0.06
8-11 MW	0.05	0.04	0.02	0.04
11+ MW	0.07	0.09	0.06	0.09
Countries	17	17	17	17
Observations	230,540	913,694	92,715	364,972

The table presents means of household and survey respondent demographic characteristics using data from the online survey and nationally representative surveys, and pooling observations from all study countries (weighting by country size). Column (1) reports raw means using all the observations from the online surveys. Column (2) reports means using all available observations in the household (field) surveys using sampling weights. Column (3) reports means from the online survey data using only data from the testing sample (i.e., the sample not used for the estimation of the inverse probability weights). Column (4) reports means using data from the household (field) surveys corresponding to the testing sample. The testing sample corresponds to a randomly selected subsample corresponding to 40% of all the observations in the online and household (field) surveys. MW stands for national minimum wage. The inverse probability weights are computed based on logit models of the probability of being observed in the household survey which are estimated country by country. The models include including age, gender, and education categories of the respondent as well as household-level demographic characteristics such as the presence of children younger than 5 years old, the presence of elderly children in the household, # of children enrolled in school, household size, as well as region fixed effects.

TABLE S4 Loss of livelihoods and changes in well-being, and policy support (unweighted results)

	Panel A: Locality X date Fixed effects - unweighted					
	(1)	(2)	(3)	(4)	(5)	(6)
	Decreased income	Went hungry	Eats less healthy	Gift/Loan	Gov. Priority	Lockdown (>= *month*)
Lost job or closed business	0.293***	0.096***	0.073***	0.213***	-0.026***	-0.030***
	(0.007)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Observations	188152	200594	176198	200421	198410	125359
Adjusted R2	0.235	0.140	0.036	0.157	0.035	0.430
	Panel B: Country X date fixed effects (weighted)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Decreased income	Went hungry	Eats less healthy	Gift/Loan	Gov. Priority	Lockdown (>= *month*)
Lost job or closed business	0.245***	0.162***	0.069***	0.216***	-0.036***	-0.008
	(0.021)	(0.025)	(0.016)	(0.018)	(0.008)	(0.018)
Observations	202832	215410	190065	215236	213188	139800
Adjusted R2	0.266	0.244	0.097	0.192	0.110	0.111
	Panel C: Country X date fixed effects (unweighted)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Decreased income	Went hungry	Eats less healthy	Gift/Loan	Gov. Priority	Lockdown (>= *month*)
Lost job or closed business	0.291***	0.100***	0.074***	0.212***	-0.026***	-0.031***
	(0.023)	(0.010)	(0.005)	(0.009)	(0.003)	(0.008)
Observations	204464	217249	191801	217075	214980	141617
Adjusted R2	0.236	0.124	0.031	0.149	0.026	0.026
	$*p < 0.1, **p < 0.05, ***p < 0.01$					

Panel A reports unweighted regression coefficients capturing the relationship between livelihood losses during the pandemic and outcomes. Each column reports results of a regression of the dependent variable on an indicator of whether any household member either lost a job or closed a business and a vector of covariates. In addition, all regressions control for locality × day of survey completion fixed effects (18,764), as well as economic-sector fixed effects. Standard errors are clustered at the locality level (3,165). Panels B and C replicate the results using country-date fixed effects (300) and standard errors clustered at the country level (17). See the Empirical Methods section in the main text for more details.

TABLE S5 Impacts of livelihood loss on income and food security by labor market characteristics

Panel A: Impacts on food security by country-level rates of self-employment			
	(1)	(2)	(3)
	Decreased income	Went hungry	Eats less healthy
Lost job or closed business × % Self-Employed	-0.006***	0.002***	0.000
	(0.001)	(0.000)	(0.000)
Lost job or closed business	0.488***	0.019	0.066***
	(0.022)	(0.020)	(0.022)
Observations	186,521	198,726	174,452
Adjusted R-squared	0.437	0.545	0.350
Panel B: Impacts on food security by country-level rates of informality			
	(1)	(2)	(3)
	Decreased income	Went hungry	Eats less healthy
Lost job or closed business × % Informal workers	-0.003***	0.002***	0.001**
	(0.000)	(0.000)	(0.000)
Lost job or closed business	0.421***	0.017	0.038**
	(0.013)	(0.015)	(0.016)
Observations	179,040	190,453	166,581
Adjusted R-squared	0.416	0.548	0.355
$*p < 0.1, **p < 0.05, ***p < 0.01$			

Panel A reports regression coefficients capturing the relationship between livelihood losses during the pandemic and outcomes, as a function of the share of self-employed workers in each country. Each column reports results of a regression of the dependent variable on an indicator of whether any household member either lost a job or closed a business, and an interaction term of job loss or business closure with the share of self-employed workers in each country, and a vector of covariates. In addition, all regressions control for locality × day of survey completion fixed effects (18,764), as well as economic-sector fixed effects. Standard errors are clustered at the locality level (3,165). Panels B replicates the results using the percentage of informal workers as in each country instead of the share of self-employed workers. See the Empirical Methods section in the main text for more details.

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