4. COVID-19 and Inequality in Asia: Risks of Social Unrest?

This chapter shows, based on high-frequency labor surveys, that inequality is increasing further during the COVID-19 pandemic because job losses have been concentrated among low-income workers. Moreover, the experience from past pandemics suggests that the adverse distributional effects could be even larger in the medium term—including, looking ahead, through the displacement of low-skilled workers by robots—and that the resulting higher levels of inequality could undermine social cohesion. This is especially salient for countries with already high inequality going into this crisis. Information from the IMF Policy Tracker shows that many Asian governments have implemented significant fiscal policy measures to mitigate the pandemic's effect on the most vulnerable, with the impact depending on the initial coverage of safety nets, fiscal space, and degree of informality and digitalization. Although there is no one-size-fits-all solution, the model-based analysis shows that policies targeted to where needs are greatest are effective in mitigating adverse distributional consequences and underpinning overall economic activity and virus containment.

Labor Market Surveys Indicate Rising Inequality

The COVID-19 pandemic is taking its toll on Asia's labor market. High-frequency labor market indicators have deteriorated markedly and to a much greater extent than during the global financial crisis. Aggregate hours worked have declined both at the extensive (employment rate) and intensive margins (hours worked per employee). Unemployment has surged and labor force participation plunged—an early sign of scarring effects. As in the United States (Shibata 2020) and the United Kingdom (Haioglu, Känzig, and Surico 2020), the pandemic is worsening distributional outcomes in Asia:

- *Job losses are concentrated in industries with lower wages . . .* The crisis is affecting all industries, but high-contact sectors (such as hospitality and retail) and non-teleworkable industries (such as mining, manufacturing, and construction) are experiencing the largest declines (Figure 4.1, panel 1). These sectors have a larger share of low-skill workers and lower earnings. For example, the average monthly wage in the social sector is less than one-third that of essential and teleworkable industries.
- *. . . among women . . .* Labor force participation is significantly declining (unlike during the global financial crisis), especially for women. Between December 2019 and June 2020 Asia's female participation rate declined by 1.3 percentage points compared with a 1 percentage point fall for males (Figure 4.1, panel 2).
- *. . . and youth.* Asia had one of the highest pre-pandemic shares of youth not in employment, education, or training, particularly in developing countries. The pandemic is aggravating this trend. Asia's youth have experienced sharper job losses compared with other workers during the pandemic, and youth unemployment rose 1.4 percentage points, on average, by June (Figure 4.1, panel 3), as youth are mainly employed in high-contact sectors.

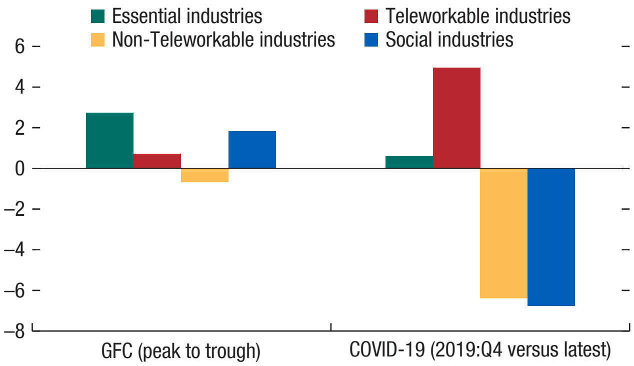
Pandemics and Automation: Will the Lost Jobs Come Back?

The COVID-19 pandemic is likely to increase inequality further over the medium term, unless policies succeed in altering historical patterns. Furceri and others (2020) provide evidence that major epidemics over the past two decades, even though smaller in scale than COVID-19, have led to persistent increases in the Gini coefficient, raised income shares to higher-income deciles, and lowered the employment-to-population ratio for those with basic education compared with those with higher education.

One channel through which pandemics may increase inequality is the acceleration in

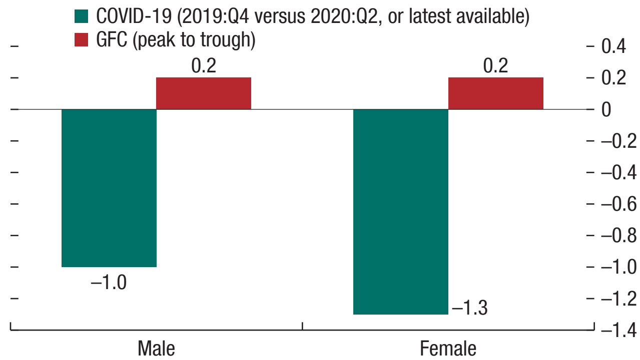
Figure 4.1. Selected Economies in Asia: Non-Teleworkable Sectors, Gender Gap, and Youth Unemployment

1. Change in Employment by Industry Classification during Crises
(Percentage points)



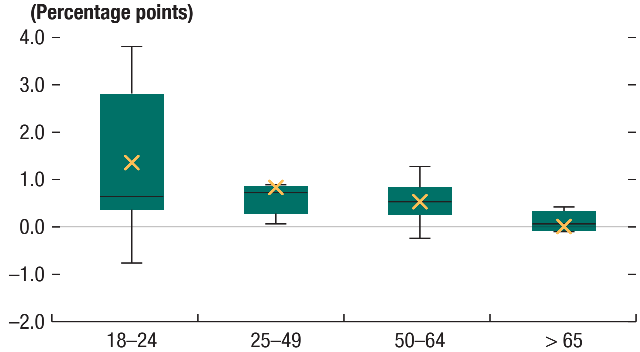
Sources: Haver Analytics; and IMF staff calculations.
Note: COVID-19 = coronavirus disease; GFC = global financial crisis. Asia refers to Australia, Hong Kong SAR, Indonesia, Japan, Korea, Malaysia, New Zealand, Singapore, Taiwan Province of China, Thailand, The Philippines, and Vietnam. Data are seasonally adjusted, based on June 2020 data (or latest available). Essential industries refer to agriculture, utilities, transport, information and communication, and health and public administration; social industries refer to wholesale and retail, hotels and restaurants, and arts and entertainment; teleworkable industries refer to finance, business and professional services, and education; and non-teleworkable industries refer to mining, manufacturing, and construction.

2. Change in Labor Force Participation Rate by Gender during Crises
(Percentage points)



Sources: Haver Analytics; and IMF staff calculations.
Note: COVID-19 = coronavirus disease; GFC = global financial crisis. Asia refers to Australia, Hong Kong SAR, Japan, Korea, the Philippines, and Thailand. Data are seasonally adjusted. For COVID-19, data are up to June 2020.

3. Change in Unemployment Rate by Age Cohort
(Percentage points)

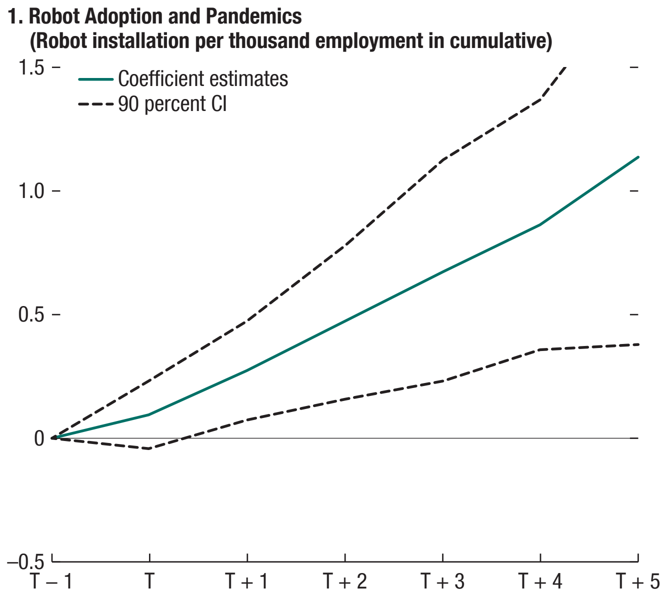


Source: Haver Analytics.
Note: Asia refers to Australia, Japan, Korea, New Zealand, Taiwan Province of China, and Thailand. Data refers to the change in unemployment rate from December 2019 to June 2020. Data are seasonally adjusted. The horizontal line inside each box represents the median; the upper and lower edges of each box show the top and bottom quartiles, respectively; and the top and bottom markers denote the maximum and the minimum, respectively. X is the mean.

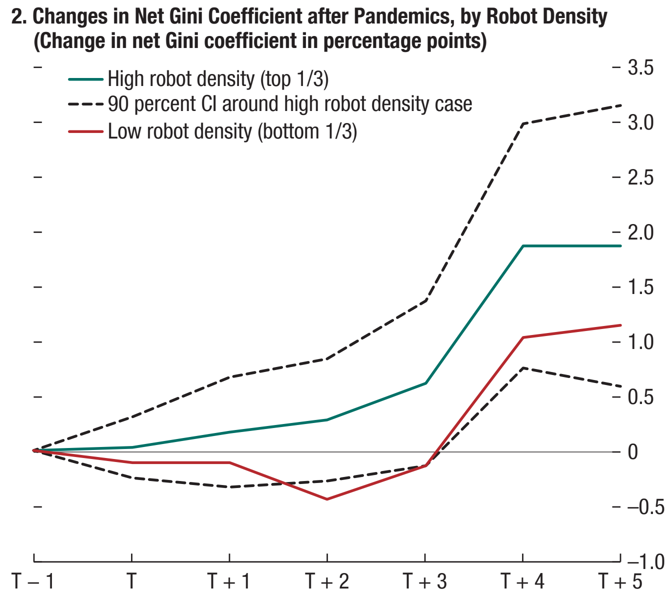
automation and robotization. Automation raises productivity, but the analysis suggests that it also increases inequality by displacing workers in routine manual occupations, which have low earnings.

Robot adoption (measured by new robot installations per 1,000 employees, collected by the International Federation of Robotics) tends to increase after pandemic events (Figure 4.2, panel 1), especially when the such events are associated with a significant economic contraction. This is in line with the literature showing that firms tend to undertake restructuring after recessions and adjust production toward labor-saving technologies (Hall 2005; Mortensen and Pissarides 1994; Hershbein

Figure 4.2. Pandemics, Automation, and Inequality



Sources: International Federation of Robotics; World Input-Output Database: Socioeconomic Accounts; Penn World Table 9.0 database; and IMF staff estimates.
Note: CI = confidence interval; T = pandemic year. Impulse responses were estimated using a sample of 14 industries in 39 economies over 2000–14 and local projection method (Jordà 2005). Right-hand scale variables are: a dummy indicating pandemic years, two lags of the left-hand scale variable, and the pandemic dummy, controlling for industry and country fixed effects; initial level of wage and capital-to-wage ratio, changes in the capital-to-wage ratio at the industry level, the country-level economic development, demographics, and measures of trade and financial globalization; and the world real GDP growth. Robust standard error is clustered at the country-industry pair level.



Sources: Standardized World Income Inequality Database; International Federation of Robotics; and IMF staff estimates.
Note: CI = confidence interval; T = pandemic year. Impulse responses were estimated using a sample of 14 industries in 39 economies over 2000–14 and local projection method (Jordà 2005), allowing the coefficients on pandemic variables to vary depending on robot density (bottom 1/3, middle 1/3, and top 1/3). Right-hand scale variables are: pandemic events, interacted with dummy variables indicating high, medium, or low robot density, controlling for country and year fixed effects; log of wage, capital-to-wage ratio, and the measures of macroeconomic development (income, demographics, measures of trade, and financial globalization). Robust standard error is clustered at the country level.

and Kahn 2018; Carbonero, Ernst, and Weber 2018). It is also consistent with recent studies showing that pandemic-induced uncertainty could add to the incentives for automation on net, despite its negative effects on aggregate demand, as firms try to anticipate future labor disruptions from pandemics (Leduc and Liu 2020).

The increase in inequality over the medium term tends to be larger for economies with higher robot density—above 2.3 per thousand (Figure 4.2, panel 2)—and where robot adoption increases more after the pandemic. These results suggest that the distributional effects of this pandemic could be sizable in Asia: In 2018 nearly two-thirds of the world's operational stocks of industrial robots were in Asia, and more than 40 percent of the world's new robots were installed in China (October 2018 *Regional Economic Outlook: Asia and Pacific,* Chapter 5). Moreover, robot density is rising fast from a low base in several Asian economies.

Pandemics and Social Unrest: When Inequality Becomes Intolerable

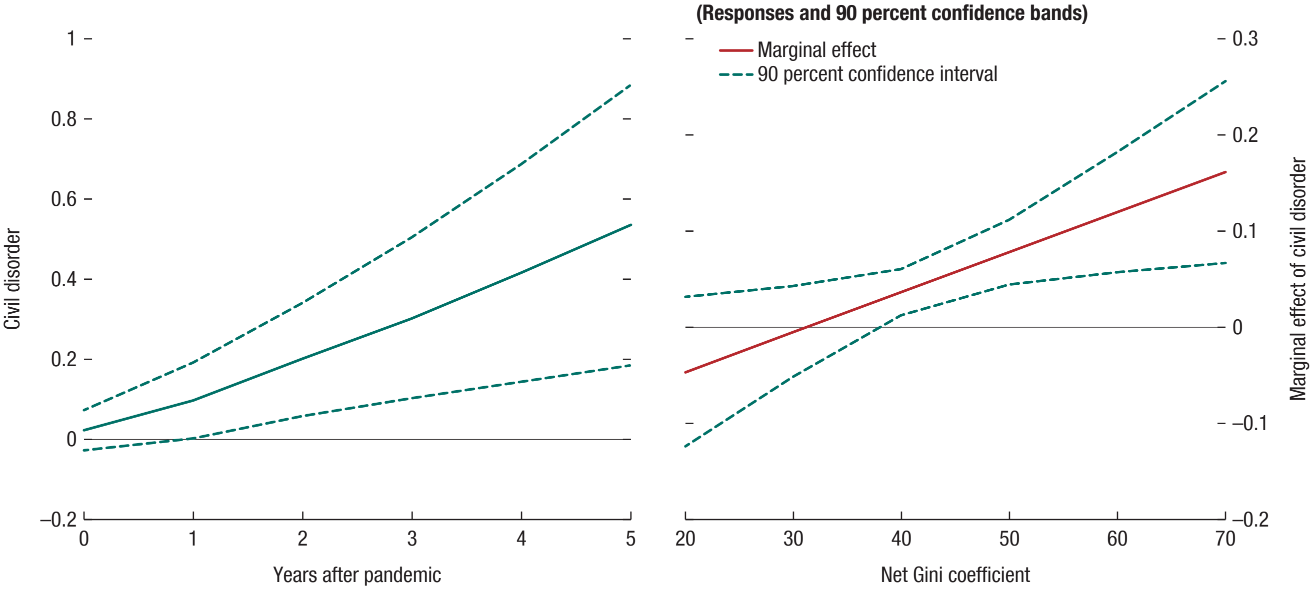
What are the implications? Higher inequality is associated with lower sustainable medium-term growth (Ostry, Berg, and Tsangarides 2014) and can fuel social tensions in countries with already high inequality.

Using a panel vector autoregression framework, it was found that past major pandemics, by reducing growth and increasing inequality, have led to a significant increase in social unrest in the medium term, as measured by the civil disorder score from International Country Risk Guide

Figure 4.3. Pandemics, Inequality, and Social Unrest

1. Impulse Response of Civil Disorder to Pandemics

2. Marginal Effect of Net Gini Coefficient on Civil Disorder (Responses and 90 percent confidence bands)



Sources: International Country Risk Guide; and IMF staff calculations.
Note: The impulse reaction functions are estimated with a panel vector autogression (VAR) model using a sample of 133 countries over 2001–18. The graph shows the responses and 90 percent confidence bands, which are estimated using Gaussian approximation based on 200 Monte Carlo draws from the fitted panel VAR model. The *x*-axis shows years after pandemic events: $t = 0$ is the year of the pandemic event. Estimates are based on the orthogonalized impulse response functions of the panel VAR model: The three endogenous variables are real growth, net Gini coefficient, and civil disorder. The pandemic dummy is an exogenous covariate in the panel VAR. Country fixed effects are controlled for, and standard errors are clustered at the country level. The sign of civil disorder is flipped so that an increase in the score indicates more disorder or higher social unrest.

Sources: International Country Risk Guide; and IMF staff calculations.
Note: The margins plot is based on a panel regression, using a sample of 133 countries over 2001–18:

$$y_{it} = \alpha + \beta_1 \cdot ineq_{i,t-1} + \beta_2 \cdot ineq^2_{i,t-1} + \beta_3 \cdot controls_{i,t-1} + \gamma_i + \eta_t + \epsilon_{i,t}.$$

Where y_{it} is the measure of social unrest, and inequality is measured by net Gini coefficient. The chart shows the marginal effects of a 1-point (out of 100) increase in net Gini coefficient on civil disorder at different levels of net Gini coefficient. Ninety percent confidence intervals are included with the point estimates. The sign of civil disorder is flipped so that an increase in the score indicates more disorder or higher social unrest.

(Figure 4.3, panel 1).[1] Higher social unrest, in turn, is associated with lower economic activity in the short term and with higher inequality. These results are consistent with the finding that external shocks raise risks to growth and social stability (Rodrik 1999).

The analysis finds that the effect of inequality on social unrest is stronger when income inequality is initially high (Figure 4.3, panel 2). An increase in the net (post tax and transfer) Gini coefficient is associated with higher social unrest when the level of the net Gini is above 40—about one-third of Asian economies have a net Gini coefficient higher than this threshold. The analysis also finds that the impact of inequality on social unrest depends on the extent of redistribution (measured as the difference between market Gini coefficient and net Gini coefficient): an increase in inequality is associated with more unrest when redistributive transfers are low, suggesting that redistributive measures indeed help to reduce social tensions.

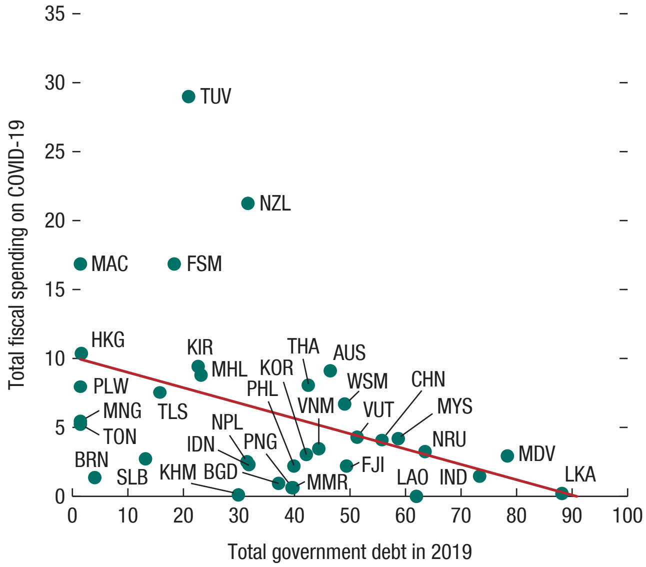
Breaking the Vicious Cycle: Policies and the Way Forward

Countries with broader social safety nets, greater fiscal space, lower levels of informality, and higher digitalization have been able to respond effectively in protecting the vulnerable, but countries that entered the crisis with weaker initial conditions faced greater challenges (Figure 4.4, panel

[1]In line with the October 2020 *World Economic Outlook*, Box 1.4, no significant short-term effects were found.

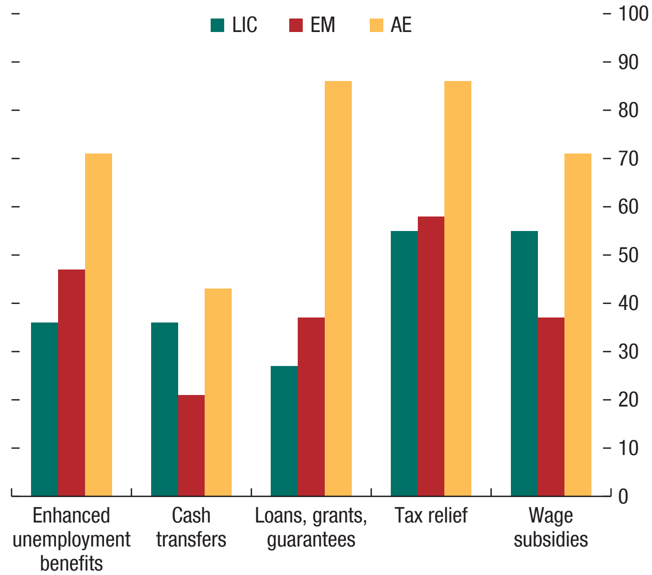
Figure 4.4. Asia's Policy Responses

1. Asia: Fiscal Response to COVID-19
(Percent of GDP)



Sources: IMF World Economic Outlook database; and IMF survey of policy responses to COVID-19.
Note: COVID-19 = coronavirus disease. Country abbreviations are International Organization for Standardization country codes.

2. Targeted Help to Households and Workers
(Percent of countries implementing the policy)



Source: IMF survey of policy responses to COVID-19.
Note: COVID-19 = coronavirus disease. AE = advanced economy; EM = emerging market; LIC = low-income country.

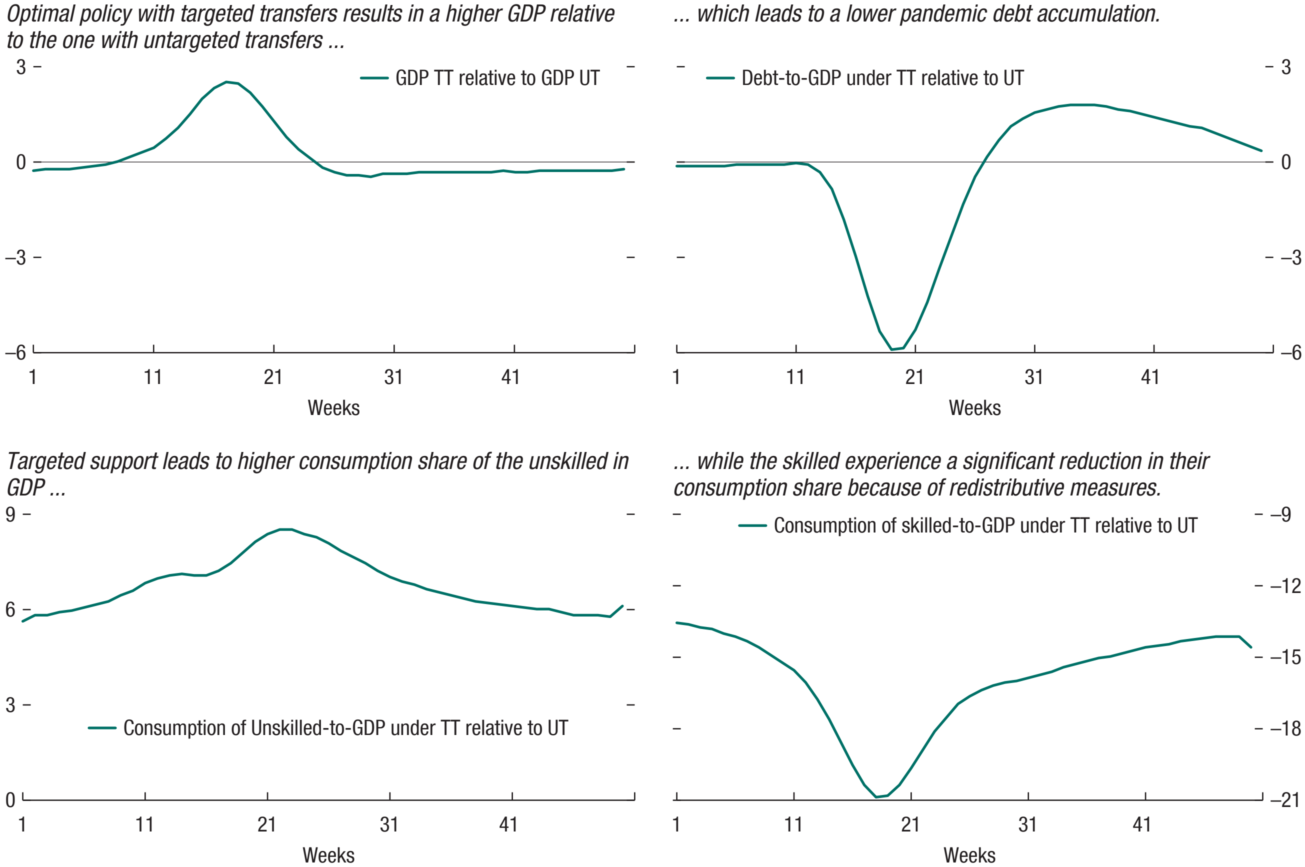
1). Advanced economies introduced targeted cash transfers more than emerging market and developing economies did (Figure 4.4, panel 2). The degree of digitalization likely played a role, helping to reach citizens in need: low-income and emerging market countries that introduced targeted cash transfers (for example, Cambodia and India, see Chapter 2) had, on average, higher digitalization scores than those that did not introduce these measures. Most advanced economies also introduced enhanced unemployment benefits, wage subsidies, and fiscal support to firms. Less frequent adoption of such measures among low-income countries and emerging markets was likely related to a higher degree of informality, which made reaching the workers and firms more challenging.

Policy Analysis: More Targeted Measures, More Lives Saved

This section compares the efficiency of various fiscal measures to alleviate the impact of the lockdown, focusing on targeted support to households. It uses a susceptible-infected-recovered macro model (Eichenbaum, Rebelo, and Trabandt 2020) extended to include both skilled and unskilled workers and external borrowing and redistributive fiscal policy (Engler and others 2020).

The analysis shows that fiscal support measures not only mitigate the economic cost of the pandemic but can significantly reduce the number of infections—about one-third relative to the no-intervention baseline. By helping to protect the livelihoods of consumers and workers and increasing their disposable income, these measures make staying home more affordable and help reinforce greater social distancing.

Figure 4.5. Targeted versus Untargeted Fiscal Support
(Differences, percent of GDP)



Source: Engler and others (2020).
Note: TT = targeted transfers; UT = untargeted transfers.

The favorable effects are larger for targeted than for untargeted measures. The former help reduce inequality in disposable income and preserve a higher consumption share of GDP for the unskilled (Figure 4.5). This saves more lives because unskilled workers tend to be more exposed to the health crisis. The reduction in infections and fatalities, in turn, helps reduce the depth of the recession and therefore flattens the surge in the debt-to-GDP ratio. The model suggests that, compared with untargeted transfers, targeted transfers raise GDP by some 3 percent and lower the debt-to-GDP ratio by 6 percentage points.

Although there is no one-size-fits-all best policy, the model suggests that it is economically and socially beneficial to provide targeted support to the unskilled. To minimize longer-term damage, policies should also address challenges from automation, including by revamping education curriculums to achieve more flexible skill sets and lifelong learning, as well as new training for adversely affected workers.