Asia and the Pacific Regional Economic Outlook October 2020

Analytical Chapter: COVID-19 and Inequality in Asia: Risks of Social Unrest?

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Outline

1. Key Inequality Trends in Asia before COVID-19
2. Rising Inequality: Evidence from Labor Market Surveys
3. Pandemics and Automation: Will the Lost Jobs Come Back?
4. Pandemics and Social Unrest: When Inequality Becomes Intolerable?
5. Breaking the Vicious Cycle: Policies and the Way Forward

Key Messages

1. Inequality has steadily increased in Asia before the COVID-19 shock, more than in other regions

2. The crisis is likely to increase inequality further in the medium term, including via an acceleration in automation

3. This may have negative consequences for social stability

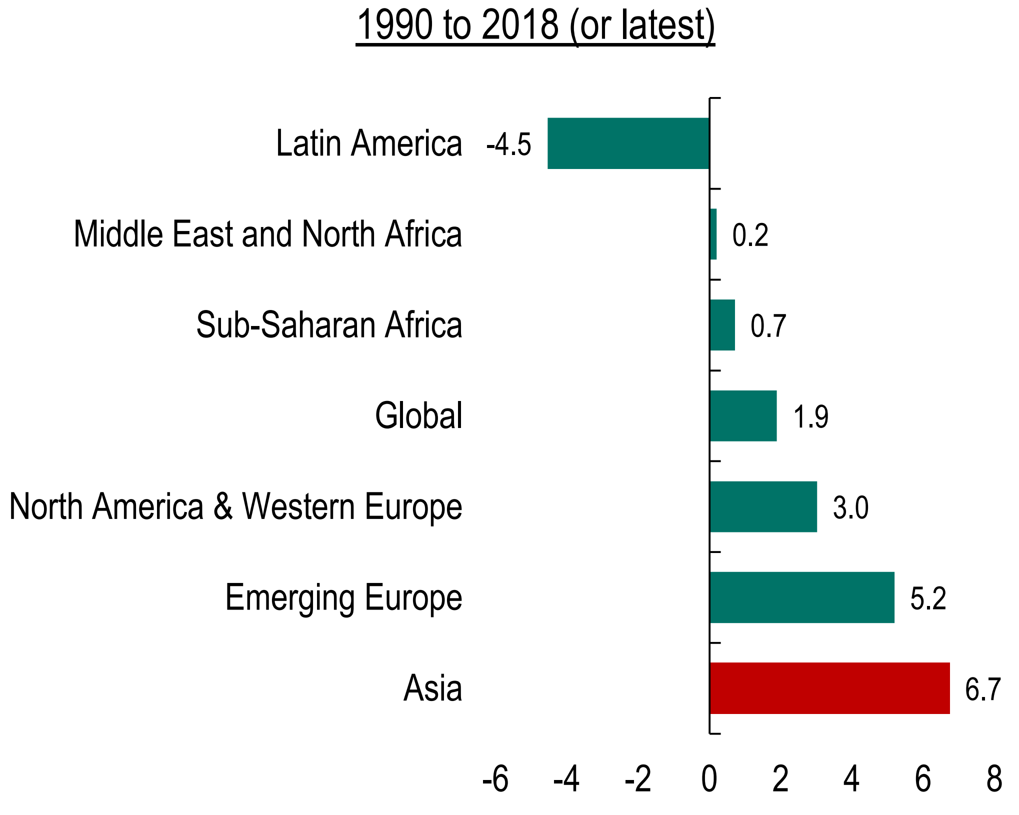
4. Redistributive policies are key to prevent such consequences and "help contribute to saving lives"

Key Inequality Trends in Asia before COVID-19

Asia's income inequality (delta) was the highest since 1990, with income growing by relatively less for the bottom decile

Change in Income Inequality: Regional Comparison

(Net Gini index, in Gini points; average across region)



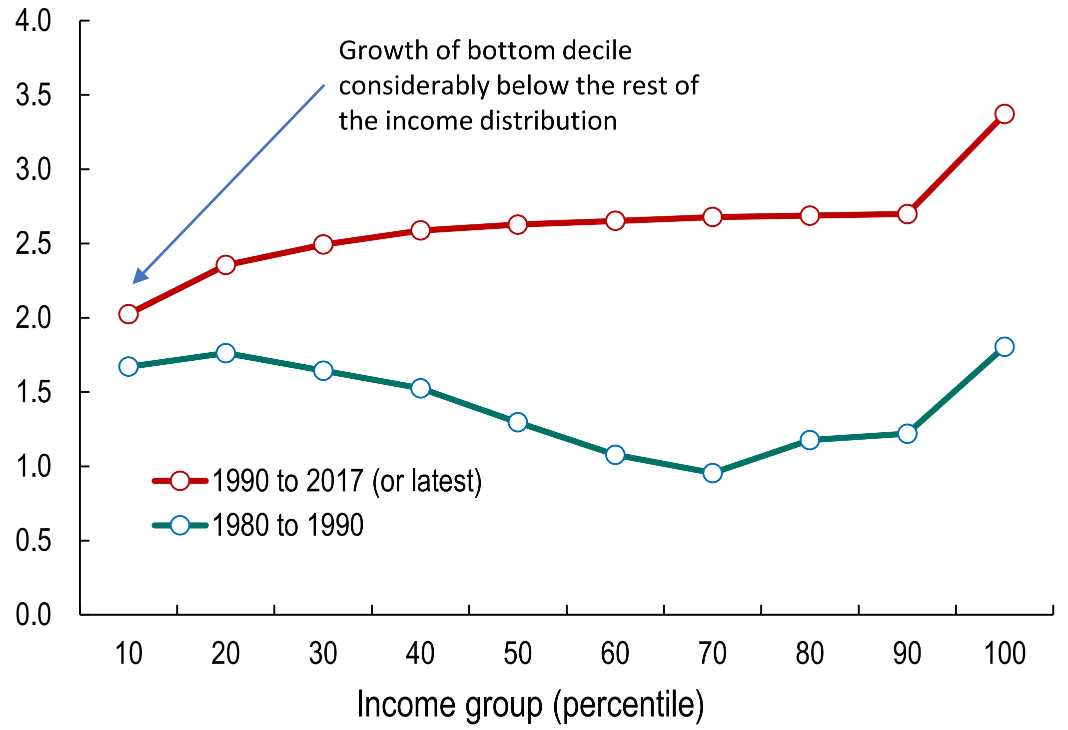
Source: SWIID v8.2, IMF staff calculations

Note: Regional aggregations are based on population-weighted average.

Asia: Growth Incidence Curve

Annual compounded mean income/consumption growth (USD), by decile

(In percent)



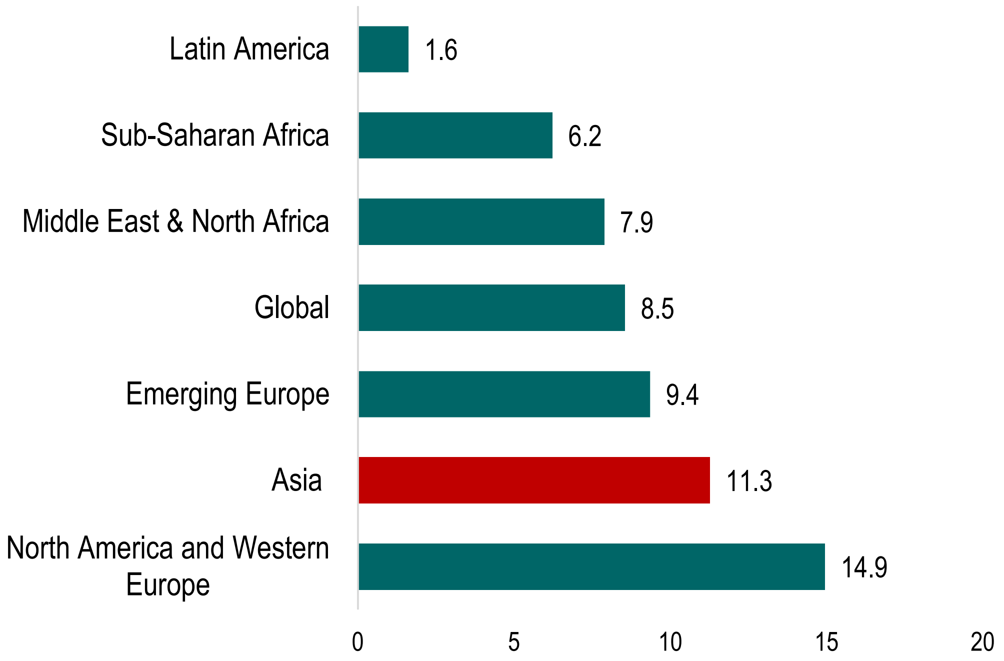
Source: World Bank PovCal database

Note: Asia refers to Australia, China, India, Malaysia, Thailand, Indonesia, Philippines, Bangladesh and Sri Lanka.

Asia had the second highest gender income gap, while the share of female youth not in employment/education was the largest

Asia: Gender Income Inequality

(Male-female gender gap: % of average male wages, 2018 or Latest)

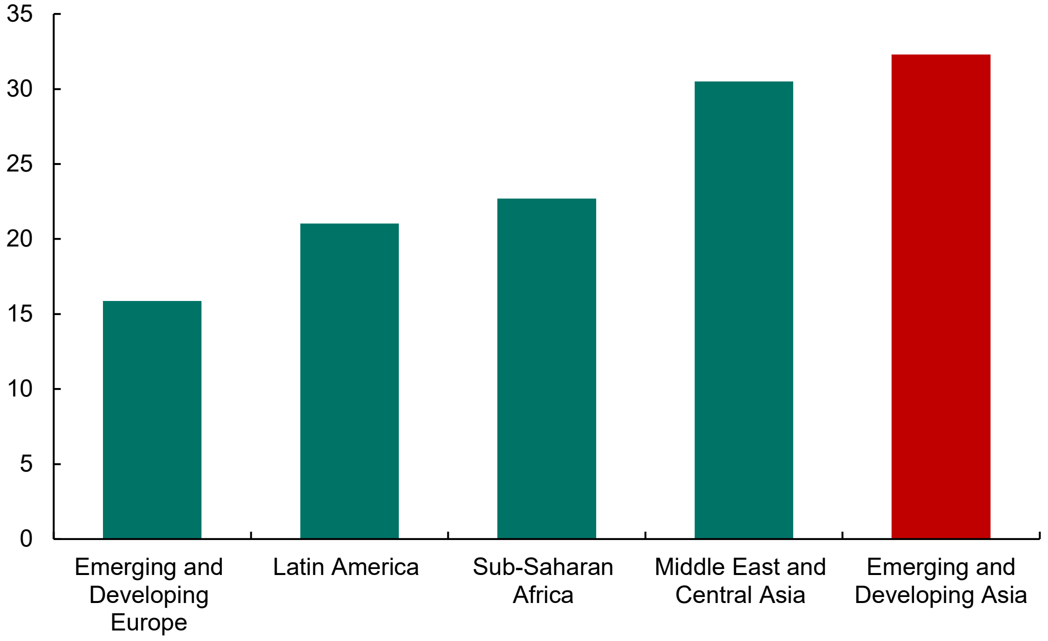


Source: ILO Stats, IMF staff calculations

Note: The data corresponds to gross hourly earnings and includes both full-time and part-time workers.

Asia: Share of Youth Not in Education, Employment or Training (NEET), Regional Comparison

(In percent)



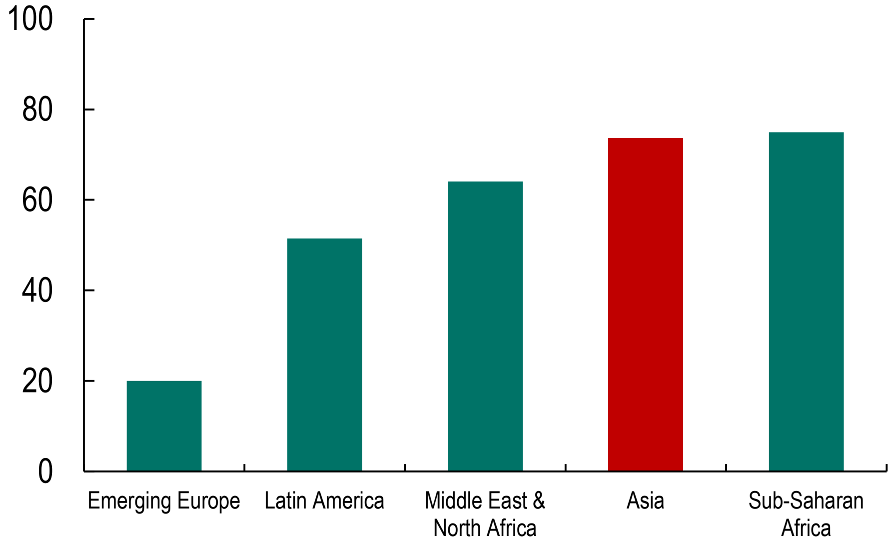
Source: ILO

Note: Aggregation for emerging and developing Europe are not available due to data gaps.

Asia's share of informality is the second highest amongst peers; its redistribution is comparatively low

Share of Informal Employment in Non-Agricultural Employment: Regional Comparison

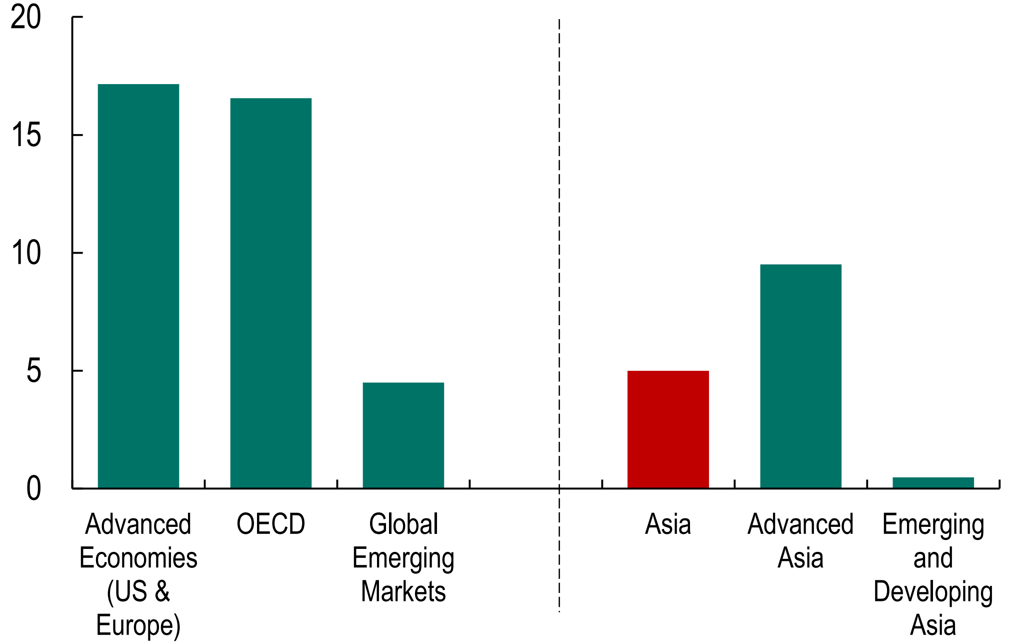
(% Share of Non-Agricultural Employment)



Source: ILO
Note: Regional aggregation is based on population-weighted average

Redistribution: Regional Comparison

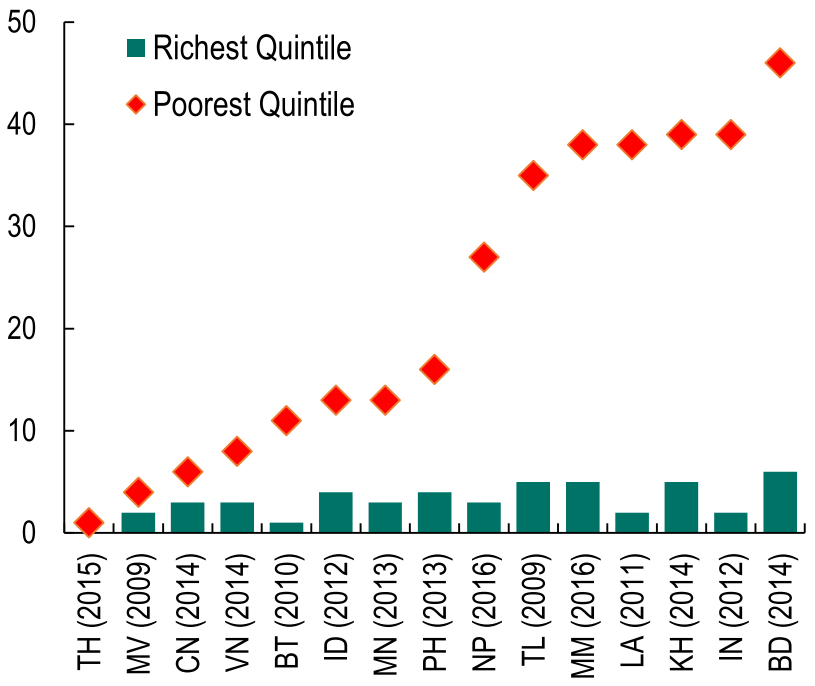
(In Gini points, 2016 or latest)



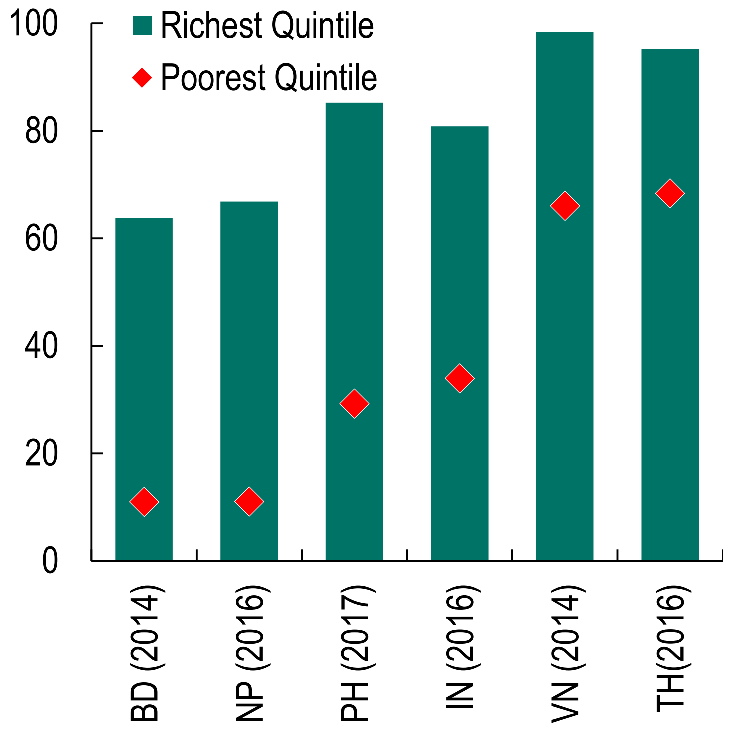
Source: SWIID v8.2, IMF staff calculations
Note: Redistribution is computed as the difference between market Gini and net Gini.

Asia is also confronted with considerable inequality of opportunities: access to education, healthcare and financial services by low-income group is limited

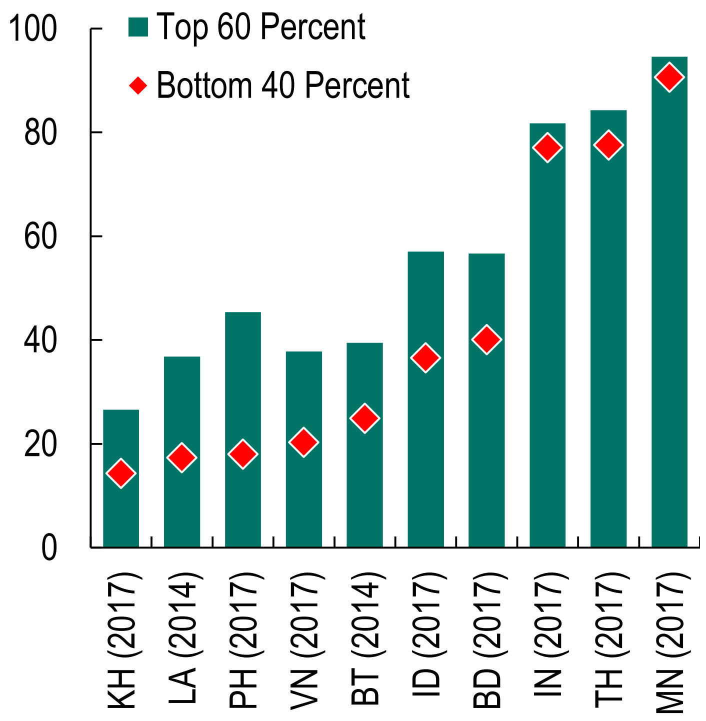
Selected Asia: Education by Wealth Quintile
(Attained less than 4 years of education, percent of total 20-24 year population)



Access to Health by Wealth Quintile
(In percent of medical interventions during child delivery)



Access to Financial Services
(Accounts at a financial institution, *in percent of total 15+ population; 2014)*



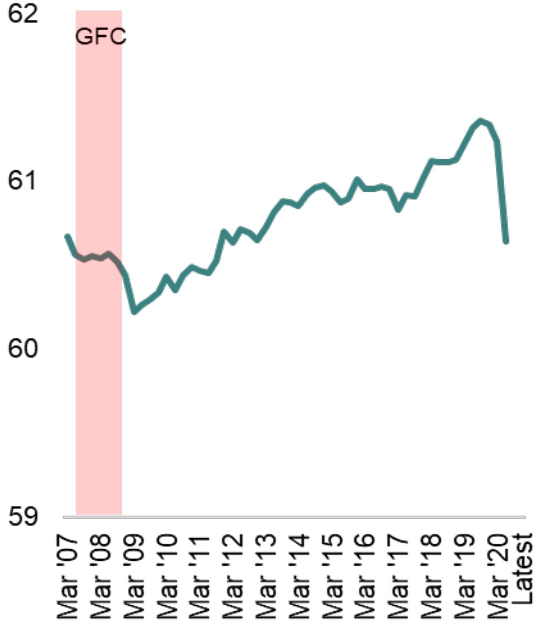
Source: World Bank, WHO Health Monitor, Global Findex Database
Note: Data refers to selected Asian economies, where data are available.

Rising Inequality: Evidence from Labor Market Surveys

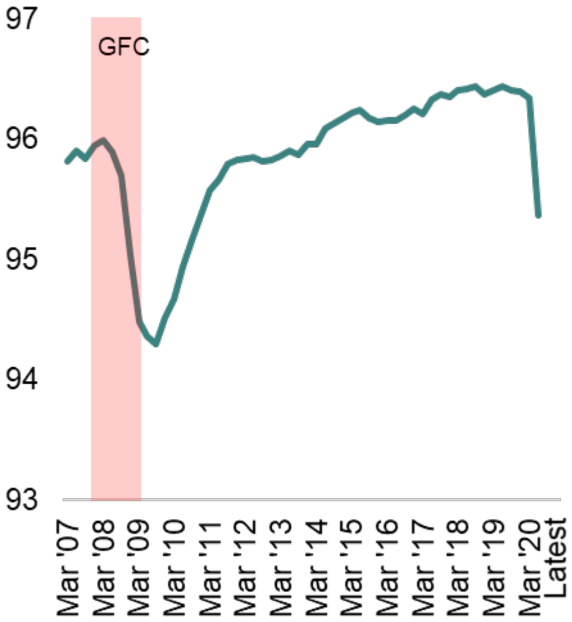
Asia's labor market indicators have deteriorated considerably, more than during the Global Financial Crisis

Asia: Key Labor Market Indicators

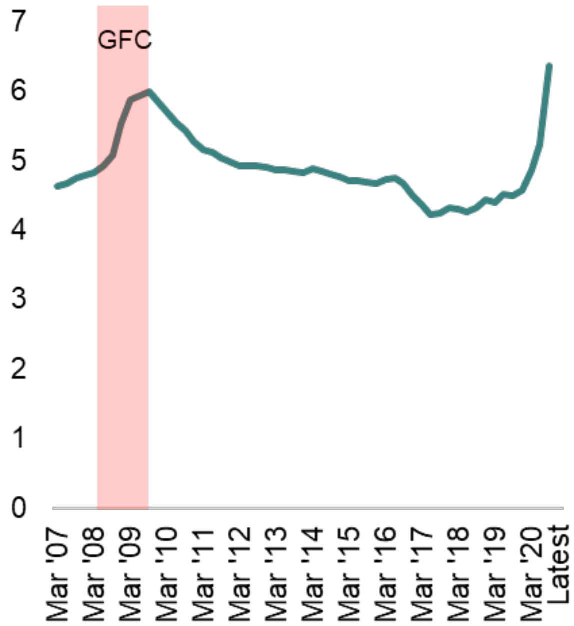
Labor Force Participation Rate
(In percent)



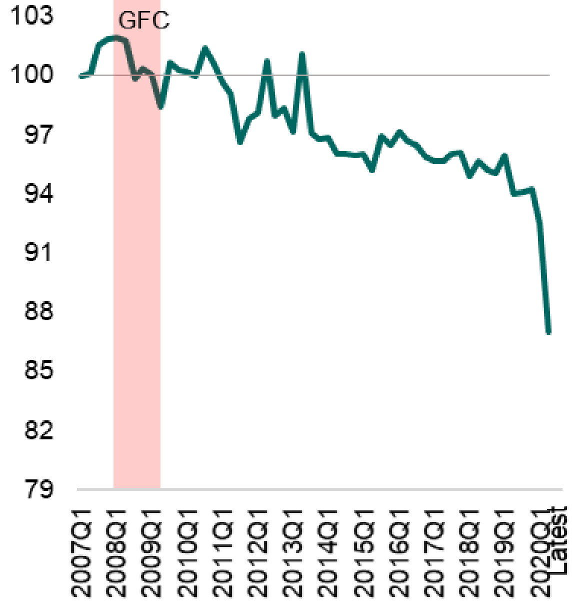
Employment Rate
(In percent)



Unemployment Rate
(In percent)



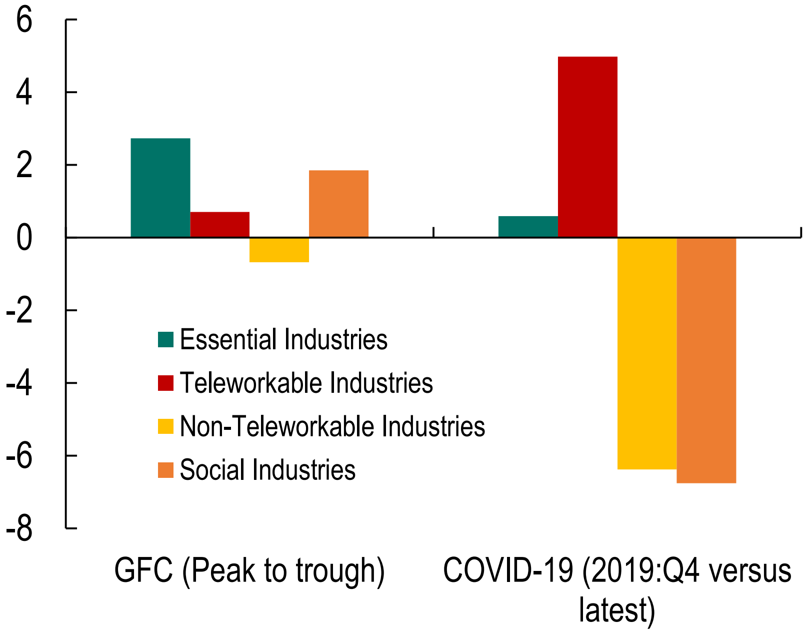
Asia: Average Weekly Hours Worked Rate
(Index Q1 2007=100)



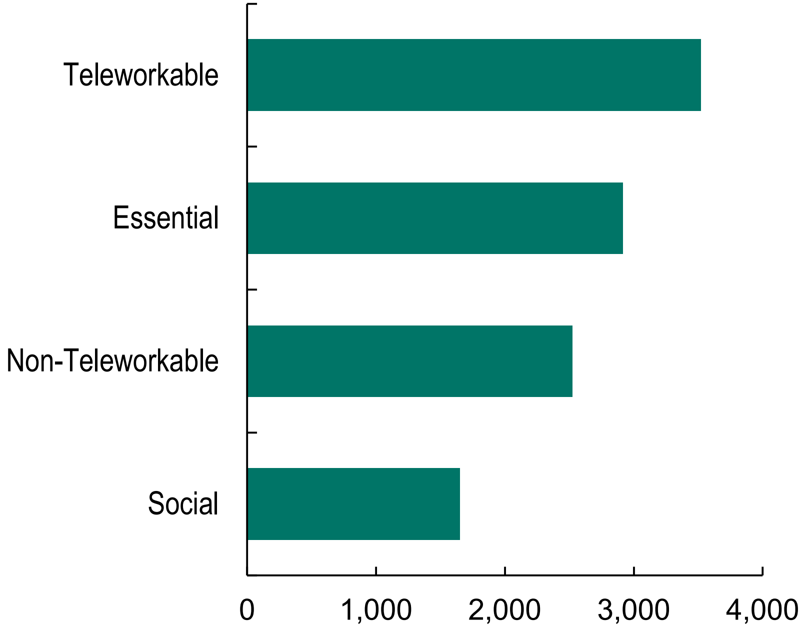
Source: Haver Analytics, IMF staff calculations
Note: Labor force participation rate, employment rate and unemployment rate for Asia refers to REO14, where available. For average weekly hours worked, Asia refers to Asia AUS, HKG, JPN, KOR, SGP and PHL only. Data are seasonally-adjusted and weighted by population.

Social and non-teleworkable industries saw the sharpest decline in employment and earnings

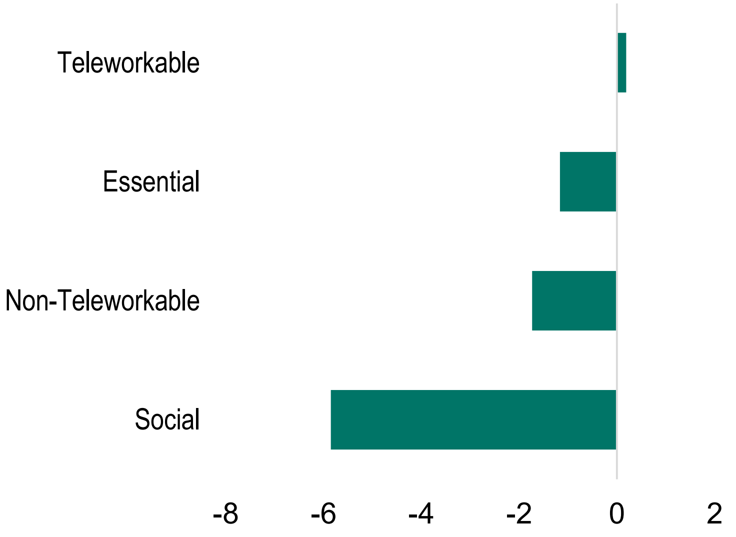
Asia: Employment by Industry Classification Delta
(in percent)



Asia: Average Monthly Wage
(Population Weighted, by industry classification, USD)



Asia: Average Monthly Wages
(% change from Pre-COVID, by industry classification)



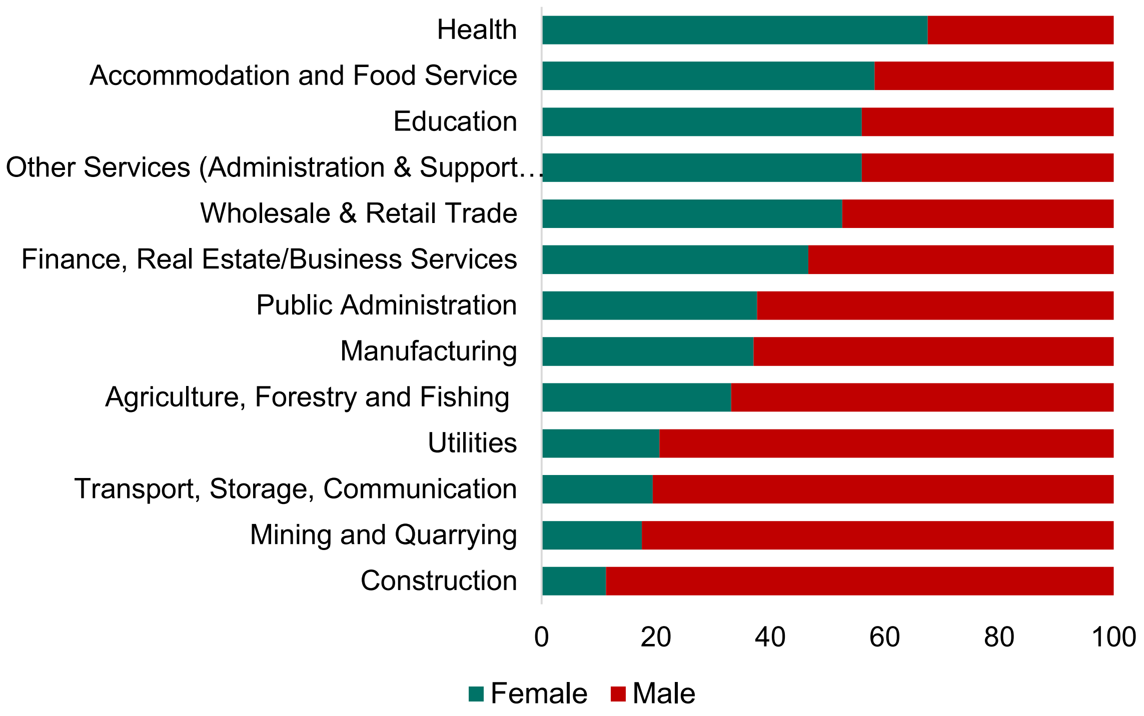
Source: Haver Analytics, IMF staff calculations

Note: Employment data for Asia refers to MYS, SGP, PHL, VNM, IDN, AUS, NZL, KOR, THA, TWN, JPN and HKG (data up to June 2020), while average monthly wages data refers to KOR, THA, TWN and JPN only (data up to April 2020). Aggregation is based on population-weighted average. 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. Reference material: "The Distributional Impact of Recessions: the Global Financial Crisis and the Pandemic Recession", "COVID-19 and Inequality in Asia: Breaking the Vicious Cycle, IMF Working Paper.

Women have been more affected by the pandemic…

Asia: Share of Employment by Gender (All Industries)

(percent)



Source: ILO, Haver Analytics, IMF staff calculations.
Note: Asia coverage: REO14, where available

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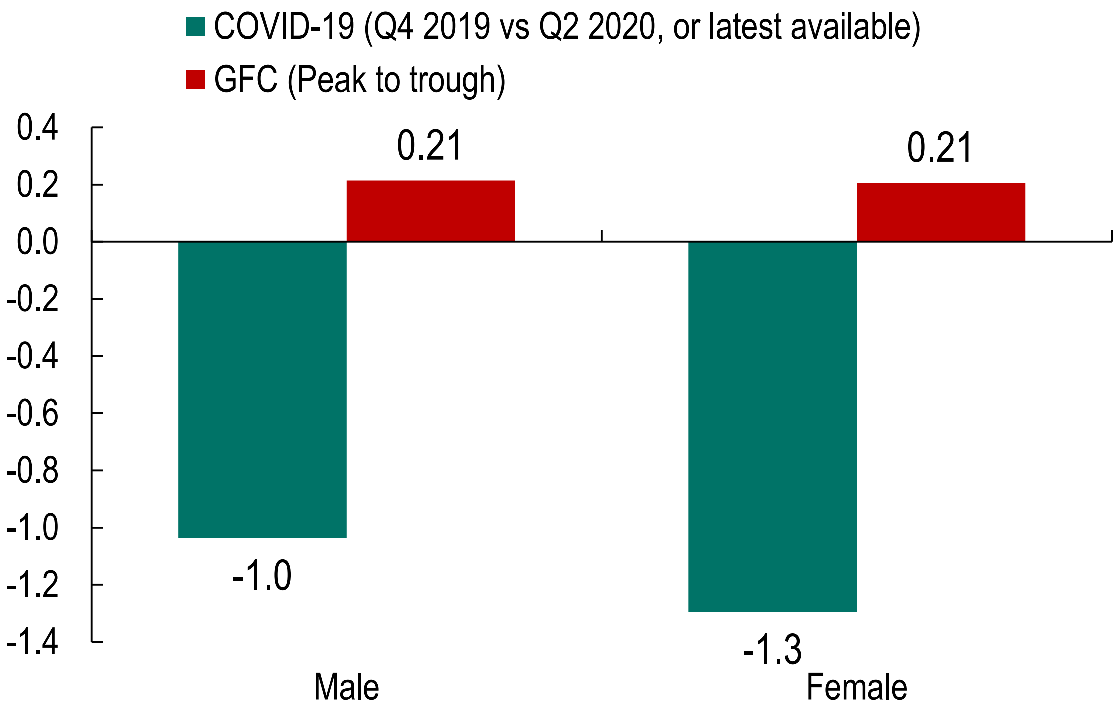
Asia: Female Labor Force Participation Rates Delta

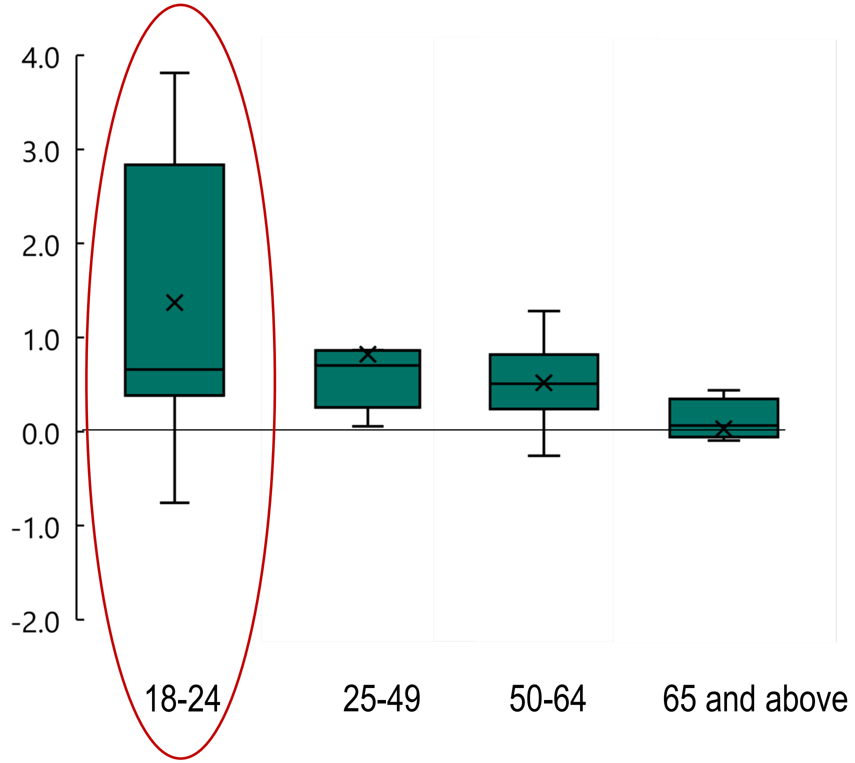
(In percentage points)



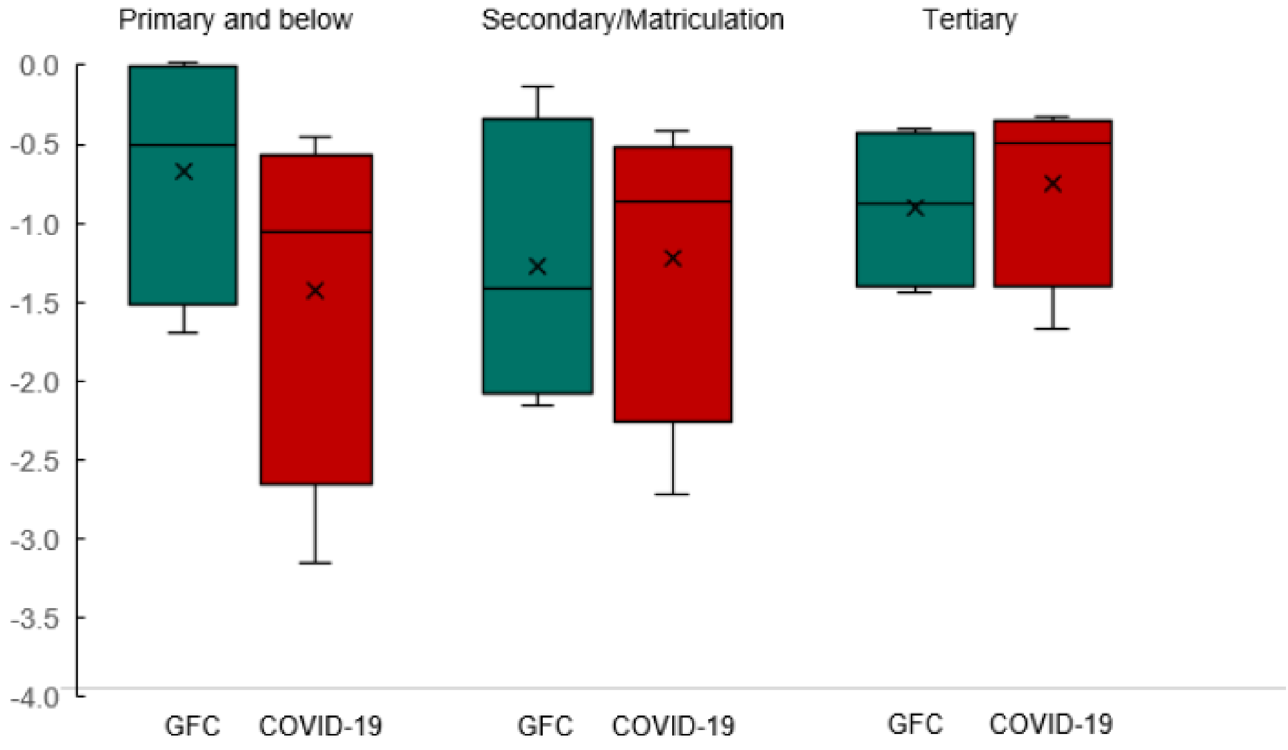
Source: Haver Analytics and IMF staff calculations
Notes: Asia refers to Australia, Japan, Korea, Hong Kong, Thailand and Philippines.
Data are seasonally adjusted. For COVID-19, data are up to June 2020.

...while younger workers and those with primary education and below were the most affected

Asia: Change in Unemployment Rate by Age Cohort
(Percentage points)



Asia: Change in Employment by Education Level
(Percentage points)



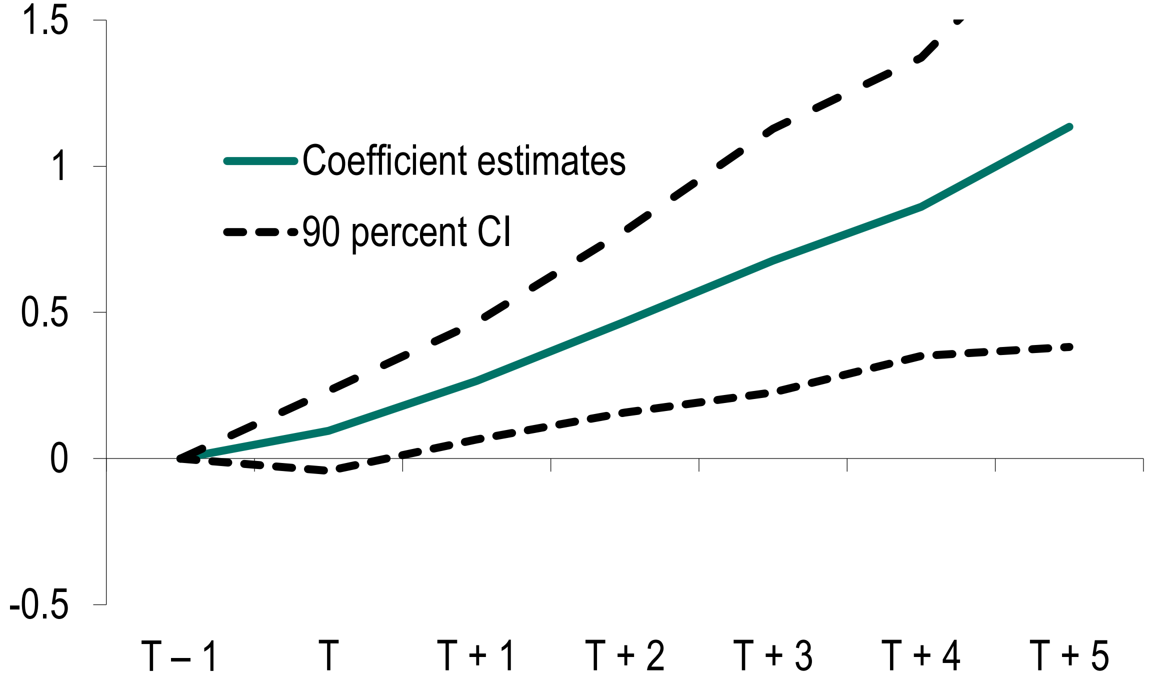
Source: Haver Analytics, IMF staff calculations
Note: Asia refers to Australia, Japan, Korea, New Zealand, Taiwan Province of China, and Thailand. Data refers to the change in unemployment rate from December 2019 to June 2020. Data are seasonally adjusted. For employment by education, Asia refers to Hong Kong, Korea, Taiwan Province of China and Thailand only. 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.

Pandemics and Automation: Will the Lost Jobs Come Back?

Increase in inequality tends to be larger for economies with higher robot density

Robot adoption and Pandemics

(Robot installation per thousand employment in cumulative; T = pandemic year)

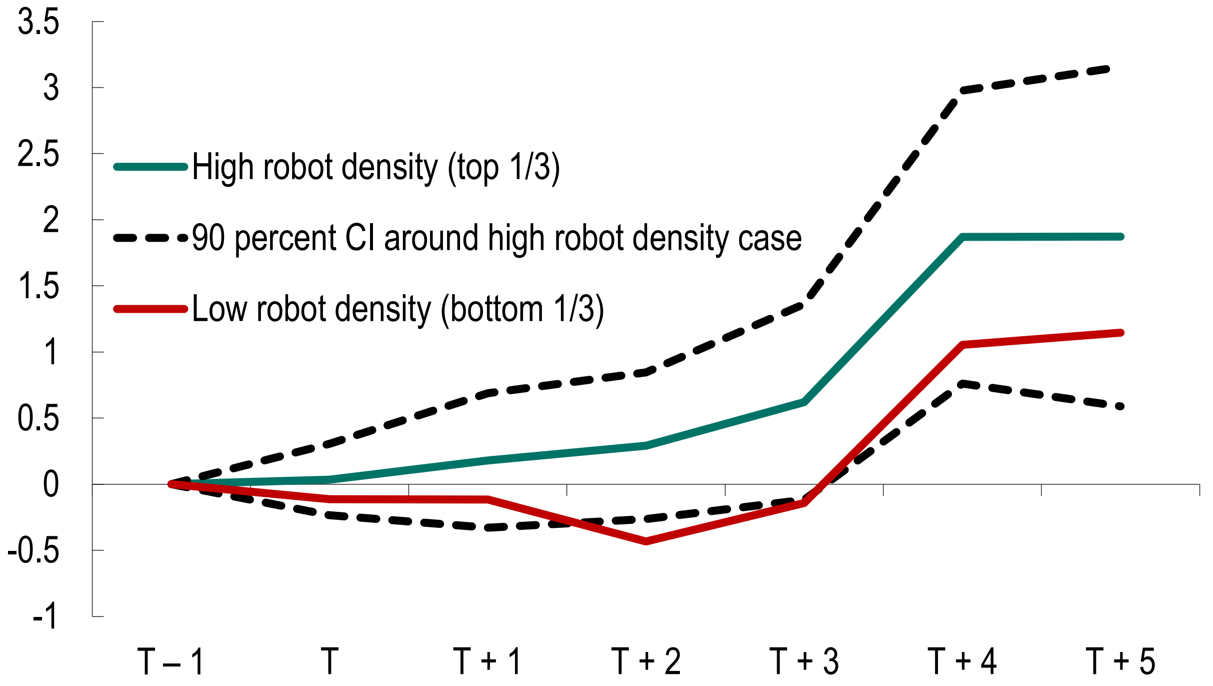


Sources: International Federation of Robotics; World Input Output Database: Socio Economic Accounts; Penn World Table 9.0; IMF staff estimates

Note: Impulse responses estimated using a sample of 14 industries in 39 economies over the period of 2000-2014 and local projection method (Jordà, 2005): LHS = robot installation per thousand employment in cumulative term; RHS = a dummy indicating pandemic years, two lags of the LHS 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

Changes in Net GINI Coefficient after Pandemics, by Robot Density

(Percentage Points)



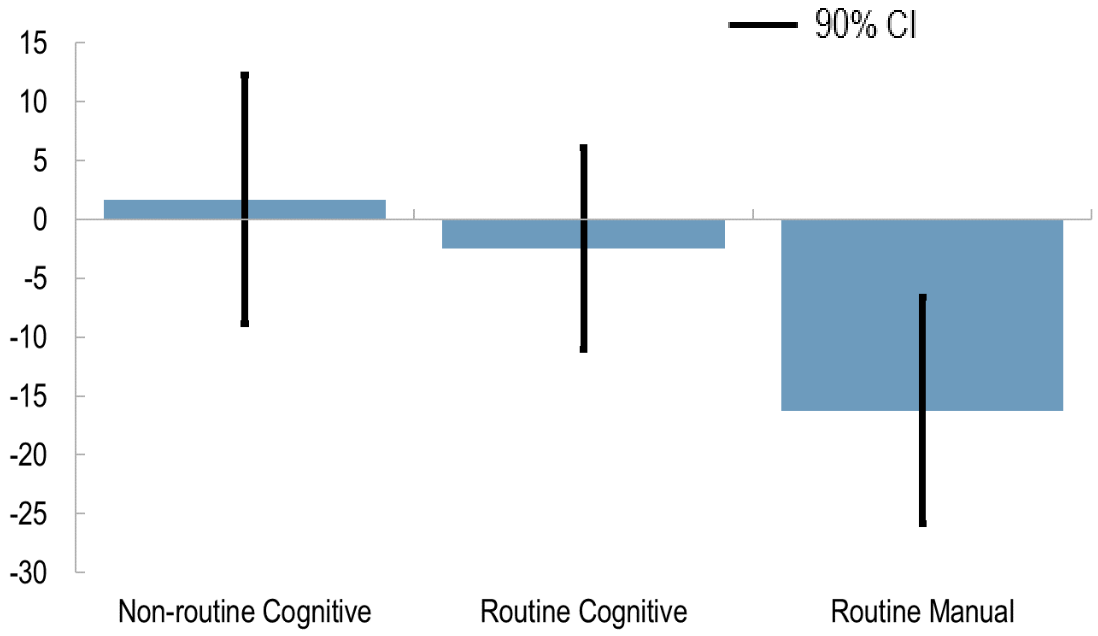
Sources: SWIID, International Federation of Robotics, PWT, Author's estimates

Note: Impulse responses estimated using a sample of 14 industries in 39 economies over the period of 2000-2014 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): LHS = net Gini; RHS = pandemic events, interacted with dummy variables indicating high/medium/low robot density, controlling for country and year fixed effects, log of wage, capital-to-wage ratio, and the measures of macro-economic development (income, demographics, measures of trade and financial globalization). Robust standard error clustered at country level.

Workers in Routine Manual occupations are most likely to lose their job to robot

Changes in Employment and Robot Adoption

(Changes in employment in percent; Estimates for the peak year)



Sources: International Federation of Robotics, International Labor Organization, WIOD, Penn World Table, IMF staff estimates
Note: The charts show the coefficient estimates on robot adoption at the peak year, estimated using a panel regression with distributed lags: LHS = changes in the employment of each occupation; RHS = robot installation per thousand employment up to five-year lags, with country fixed effects, controlling for the manufacturing industry share, wage bill, capital stock, and macroeconomic development measures (GDP per capita, urbanization, and trade and financial globalization). The confidence intervals are based on the robust errors.

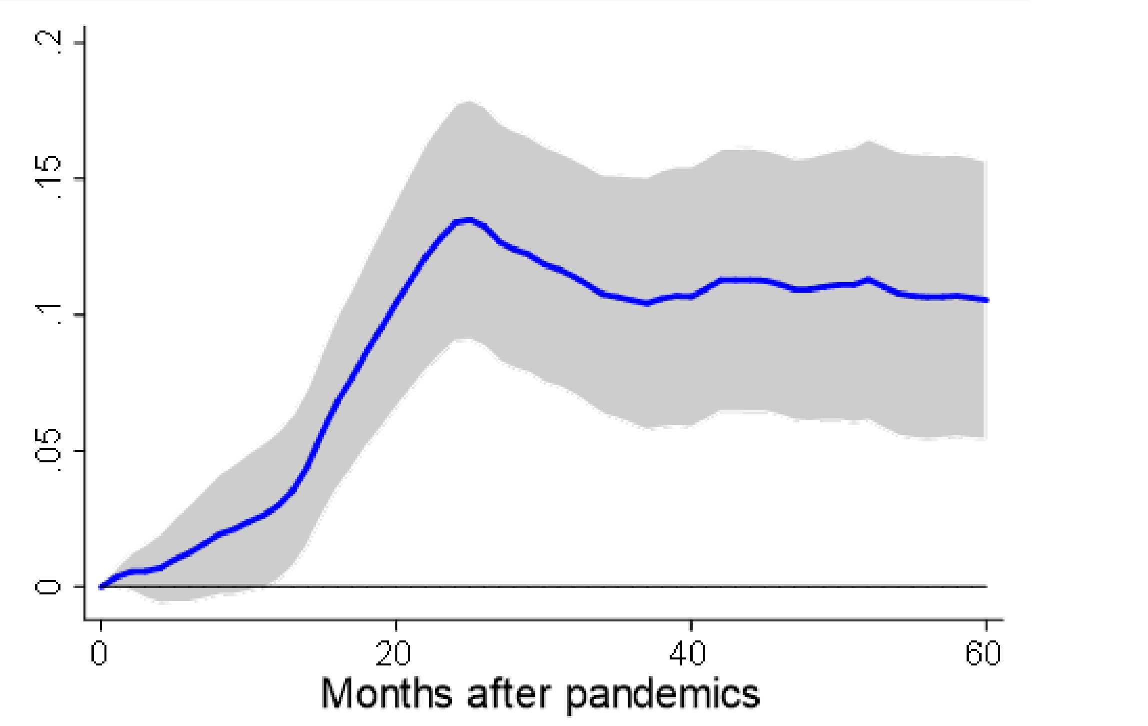
Pandemics and Social Unrest: When Inequality Becomes Intolerable?

Pandemic may turn tolerable inequalities into intolerable inequalities, and policies can perhaps help.

- Sir Angus Deaton

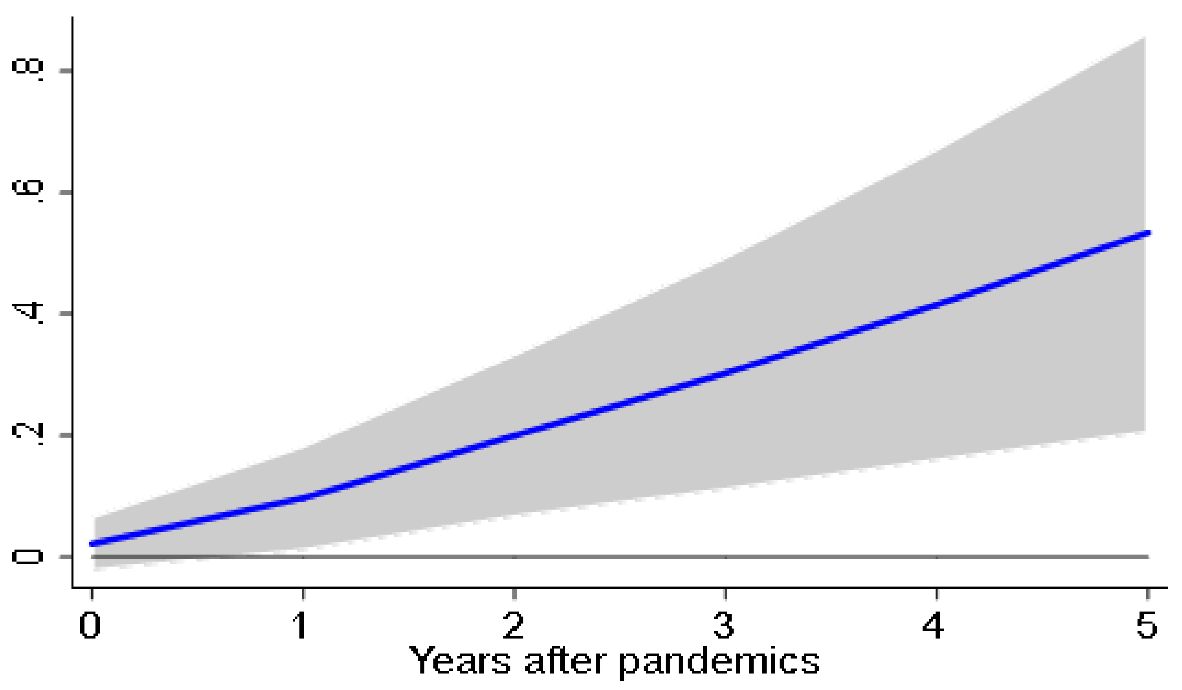
Impact of pandemic events on civil disorder: Risk of higher social unrest following pandemic

Local Projections Method using Monthly Data



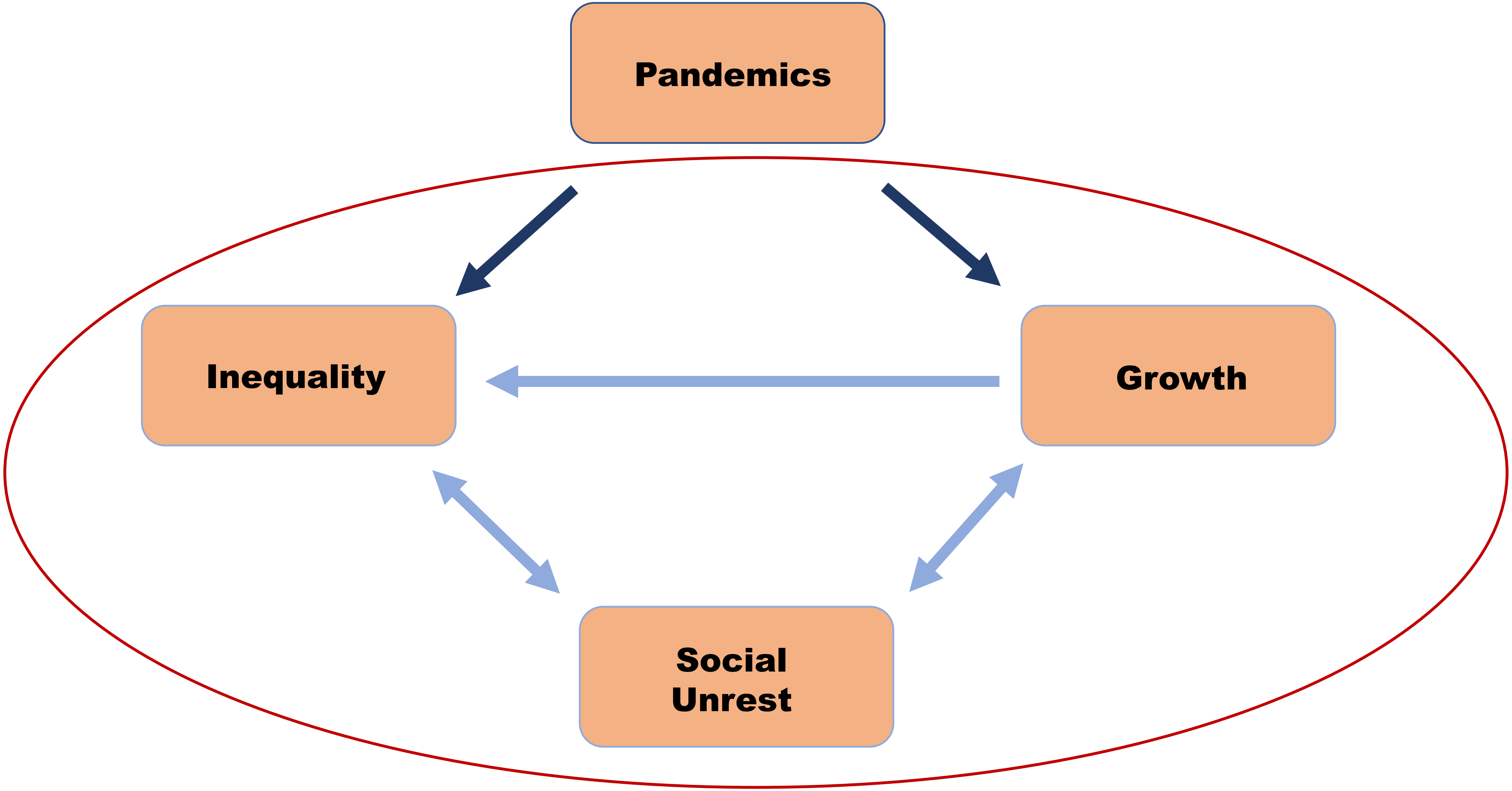
Note: The impulse response functions are estimated using a sample of 133 countries over the period of 2001-2018. The graph shows the responses and 90 percent confidence bands. The x-axis shows months after pandemic events: t=0 is the start of the pandemic event. Estimates are based on $y_{i,t+k}-y_{i,t-1}=\alpha_i^k+\beta^k D_{i,t}+\theta^k X_{i,t}+\varepsilon_{i,t+k}$. $y_{i,t}$ is the civil disorder rating for country i in month t, where a high score indicates more civil disorder; α_i are country fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in month t. $X_{i,t}$ is a vector that includes 1 to 24-month lags of the dependent variable. Standard errors are clustered at the country level. See Table A2 for the full list of pandemic events.

Panel VAR Estimation using Annual Data

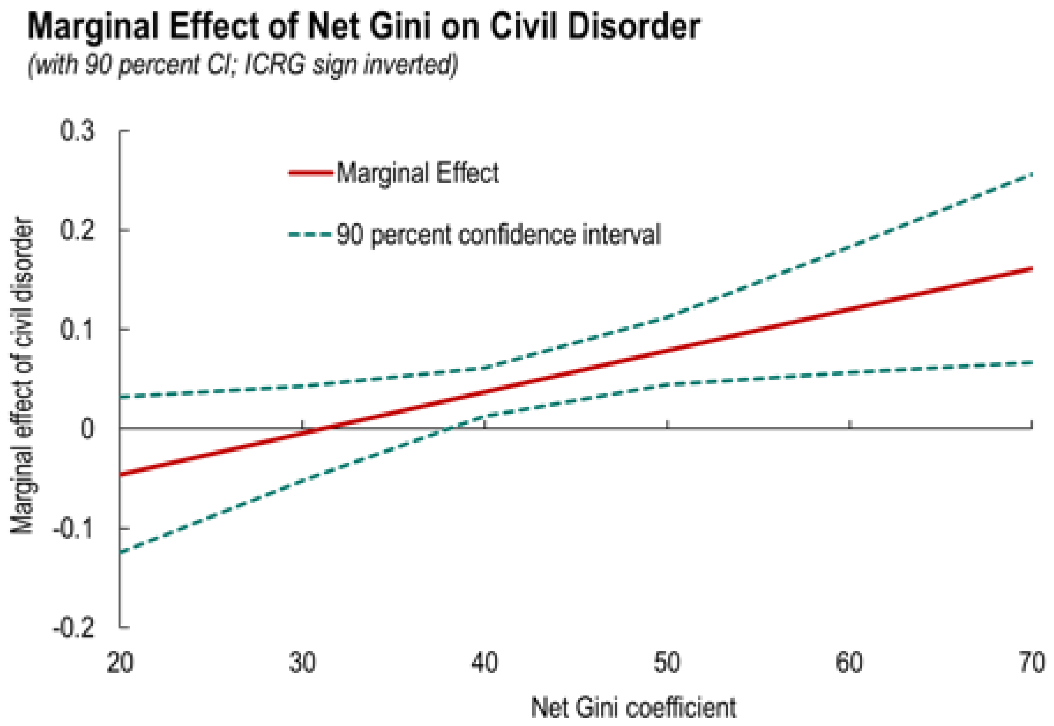


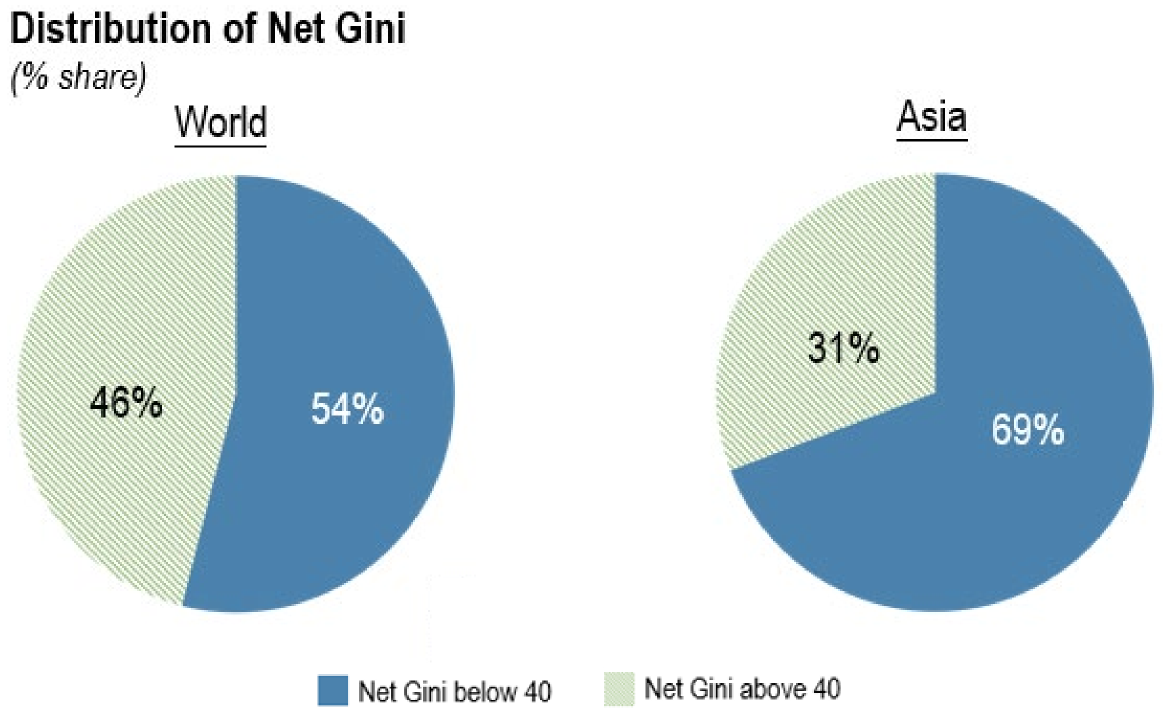
Note: The impulse response functions are estimated from Equation (2) using a sample of 133 countries over the period of 2001-2018. The graph shows the responses and 90 percent confidence bands, which are estimated using Gaussian approximation based on 200 Monte Carlo draws from the fitted panel VAR model. 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 (from most to least exogenous) are real growth, change in net Gini, 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.

A Vicious Cycle



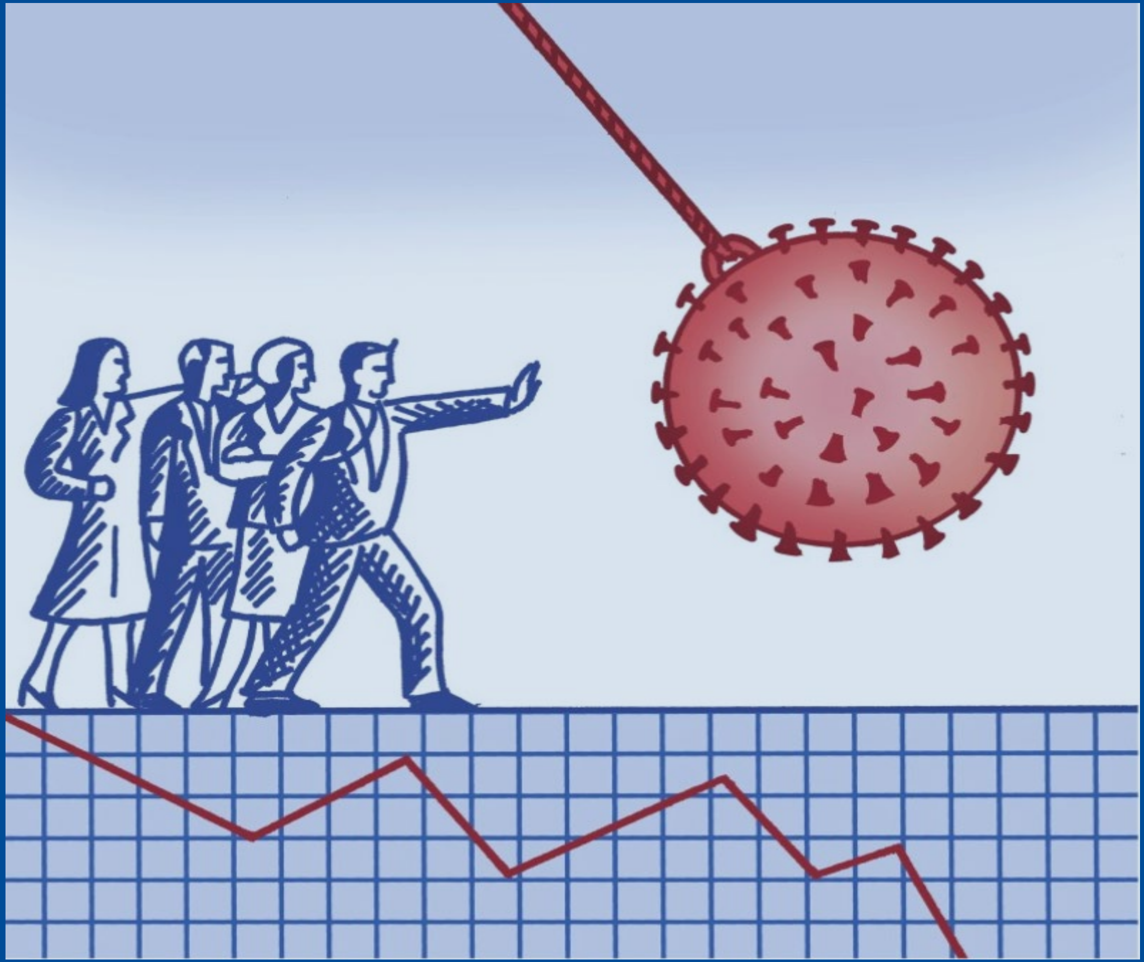
However, the effect of inequality on social unrest is non-linear





- Net Gini < 40, an increase in inequality has no effect on civil disorder;
- Net Gini > 40, an increase in inequality increases civil disorder ➔ effect increases with higher inequality
- 1/3 of Asian economies have a net Gini > 40

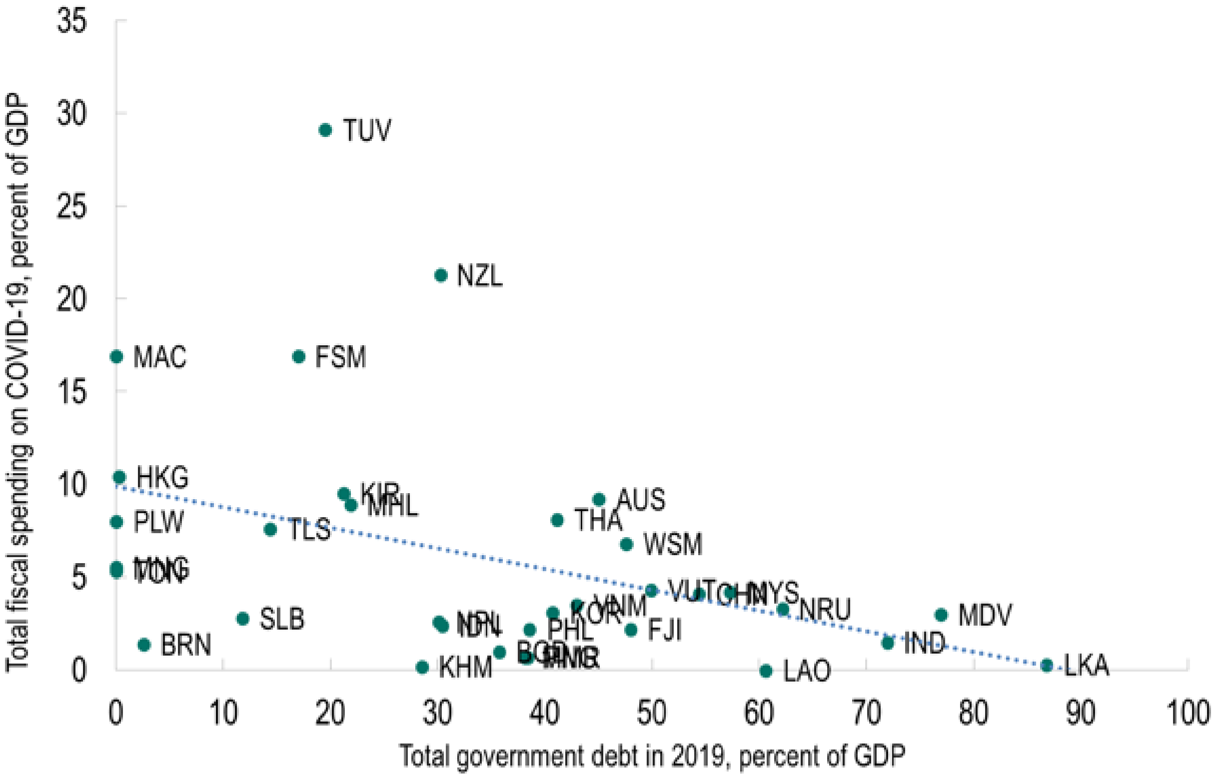
Source: ICRG, SWIID and IMF Staff Calculations.
Note: the margins plot is based on a panel regression $y_{it} = \alpha + \beta_1 \cdot ineq_{i,t-1} + \beta_2 \cdot ineq^2_{i,t-1} + \beta_3 \cdot controls_{i,t-1} + \gamma_i + \eta_t + \epsilon_{i,t}$. It shows marginal effects of net Gini on protests at different levels of Gini, with 90 percent confidence bands.



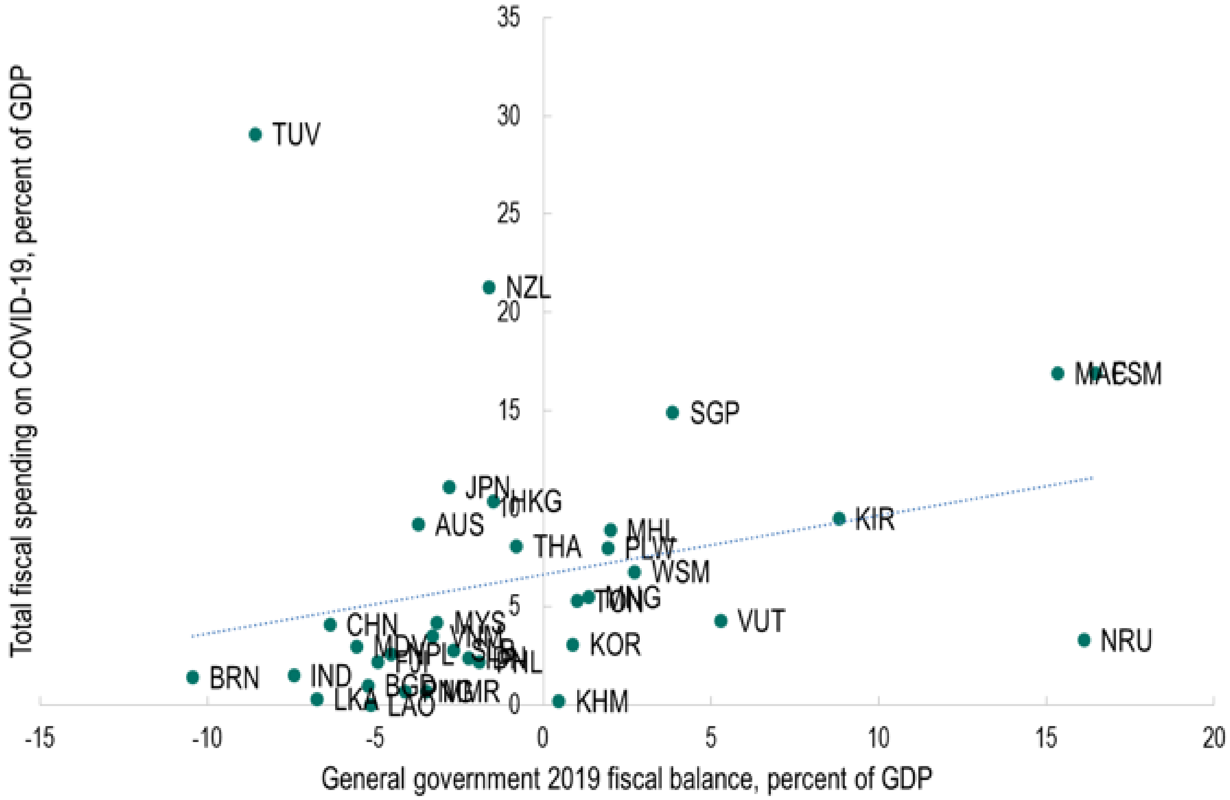
Breaking the Vicious Cycle: Policies and the Way Forward

Fiscal response to COVID-19 depended on the amount of fiscal space

Asia: Fiscal Response to COVID-19



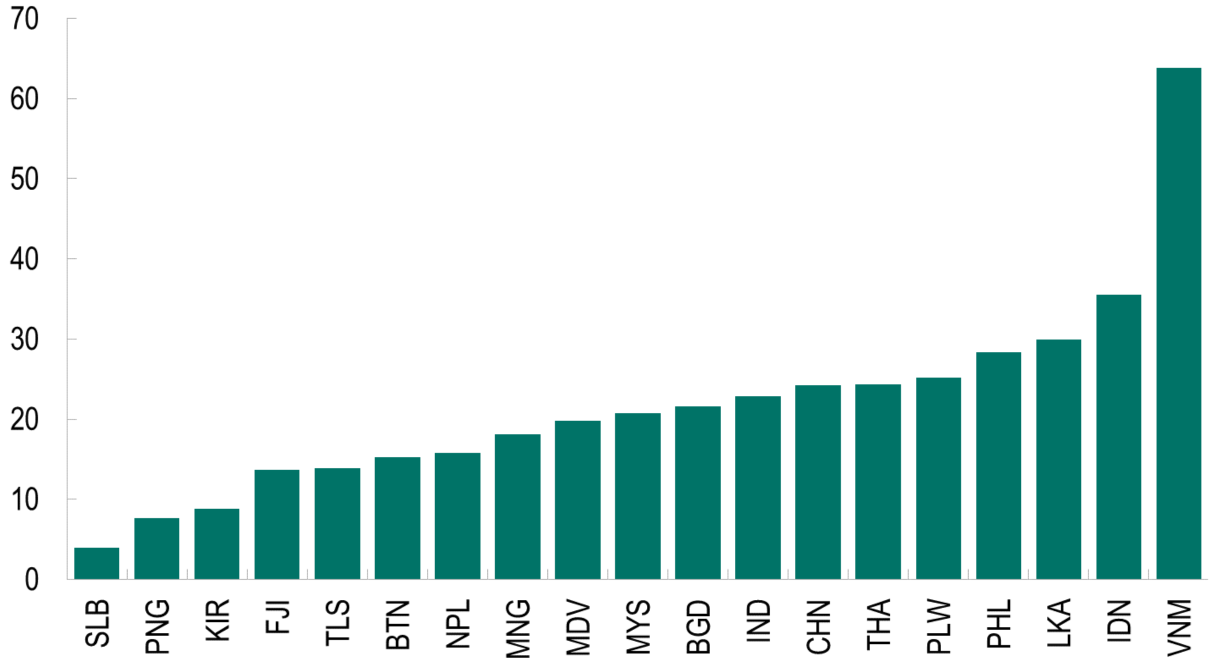
Asia: Fiscal Response to COVID-19



Source: IMF WEO Database; IMF Survey of Policy Responses to COVID-19

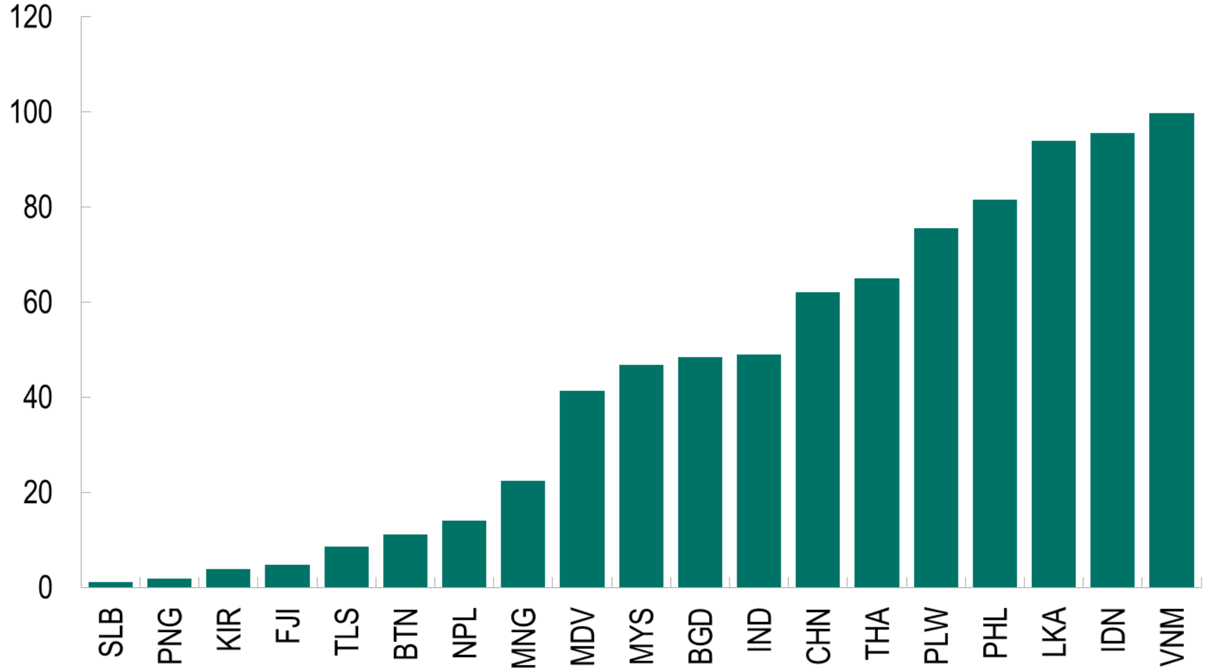
Asian countries entered the crisis with varying levels of social protection for the poorest

Asia: Share of the Poorest 25 Percent of Population Coverd by Social Assistance Benefits



Sources: World Bank ASPIRE Database

Share of the Social Assistance benefits Transferred to the Poorest 25 Percent of Population

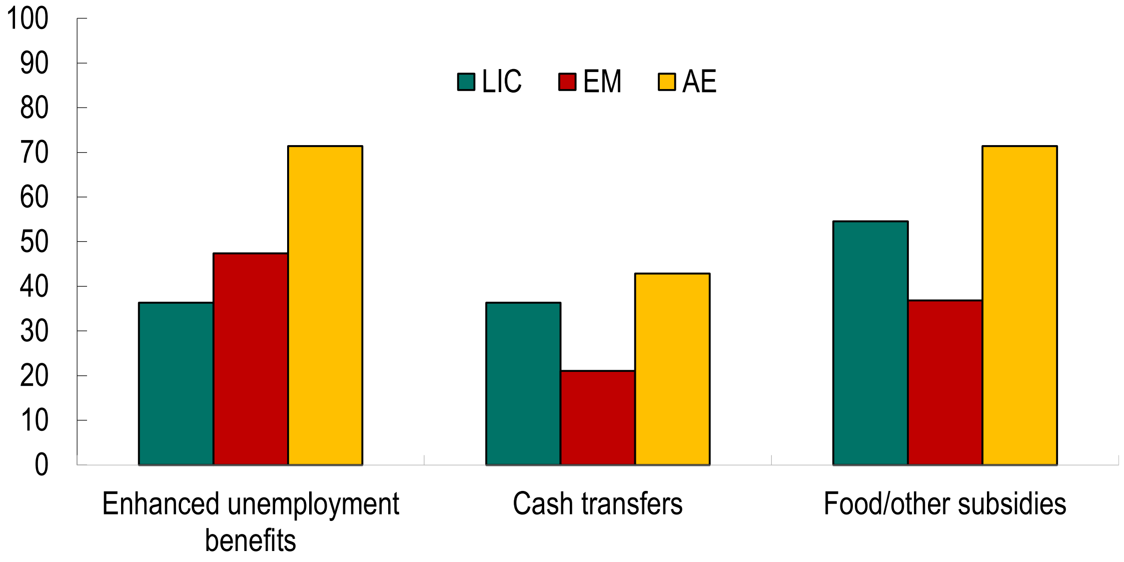


Sources: World Bank ASPIRE Database

Measures to help workers and firms depended on the state of digital adoption

Targeted Help to Households and Workers

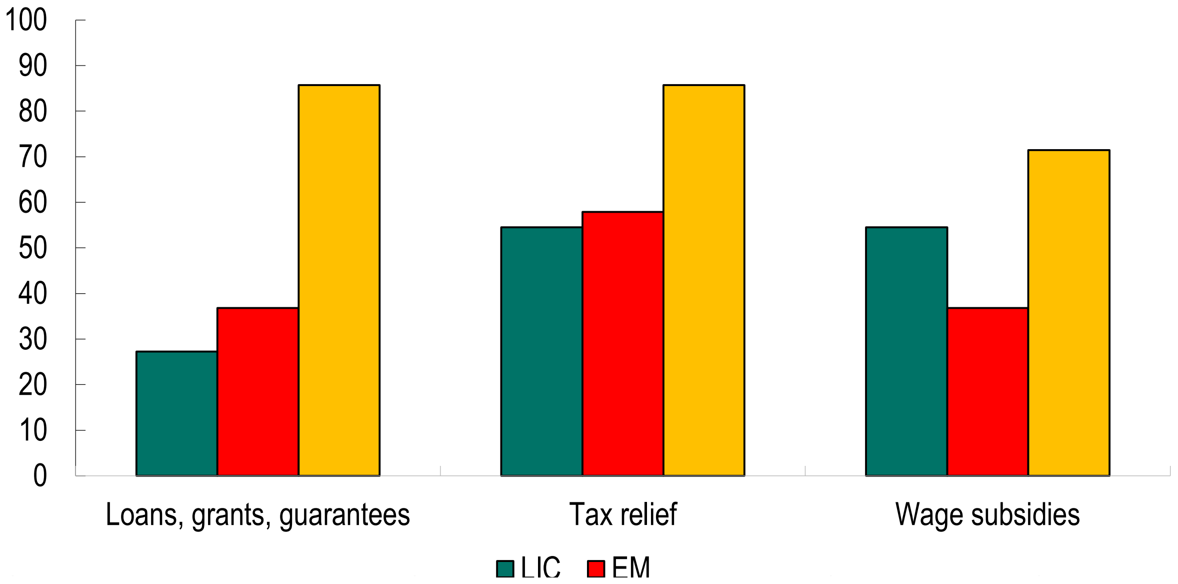
(Percent of countries implementing the policy)



	LIC		EM	
	Introduced	Not introd.	Introduced	Not introd.
	Average digital adoption index			
Targeted cash transfers	0.37	0.30	0.55	0.40
Enhanced UB	0.38	0.32	0.55	0.45
Food subsidies	0.32	0.35	0.53	0.46

Targeted Help to Firms

(Percent of countries implementing the policy)



	LIC		EM	
	Introduced	Not introd.	Introduced	Not introd.
	Average digital adoption index			
Wage subsidies	0.33	0.34	0.50	0.46
Tax relief	0.34	0.34	0.55	0.42
Loans/grans/guarantees	0.33	0.35	0.50	0.43

Sources: IMF Survey of Policy Responses to COVID-19

Note: Responses were recorded for 27 countries in APD. Countries were divided into AEs, EMs, and LICs. In each sub-group, solid bars indicate the number of countries that introduced a given policy while shaded bars the number of countries that didn't introduce it. Higher value of digital adoption index signifies higher degree of digitalization.

Targeted fiscal support is key given limited fiscal space

Targeted fiscal support measures save lives

But the additional, fast build-up of debt poses risks to fiscal sustainability

Model:
SIR + Macro + Inequality + Optimal Fiscal Policy + Debt

SIR : Susceptible + Infected + Recovered (SIR) + Dead

Virus : Consumption + workplace + general community spread

Macro : Optimal consumption and labor supply decisions by each SIR consumer

Inequality : Inequality of income, skilled workers earn higher wages

Fiscal : Fiscal instruments

➔ Progressive labor income taxes + general or targeted transfers to the skilled and unskilled

Debt : An external pandemic bond repaid after the pandemic is over

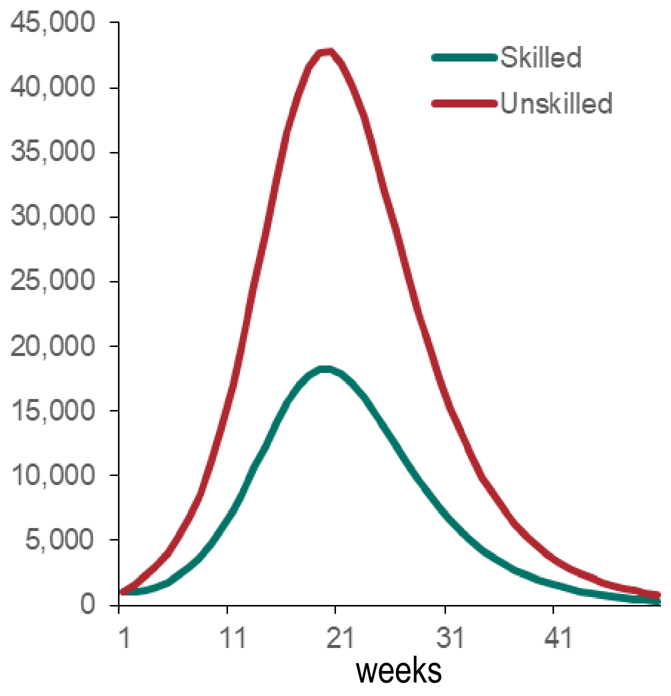
Source: Engler, Rodriguez Guzman, Pouokam, and Yakadina (2020)

Model simulations:

Matching Pandemic Behavior of Different Income Brackets

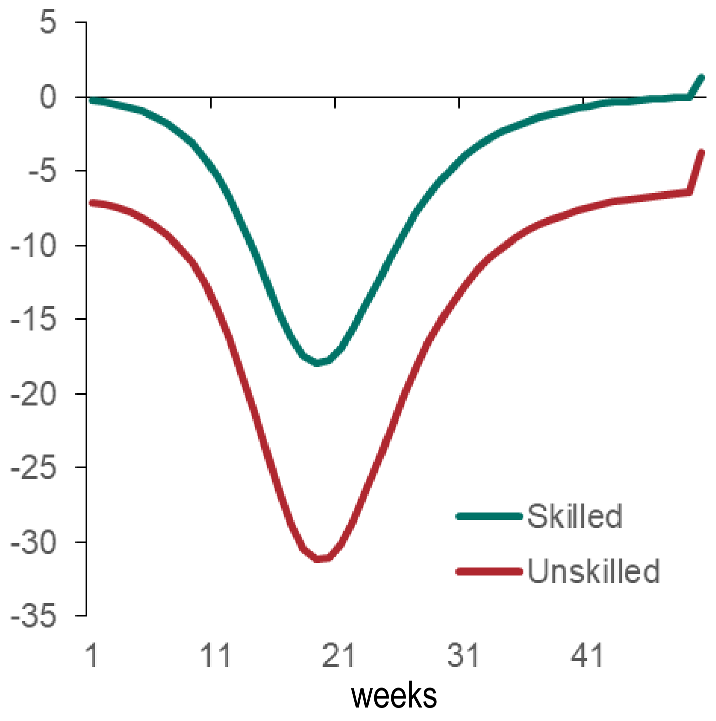
The unskilled are more exposed to the pandemic through their workplaces

Confirmed New Cases
(per million)



Lower income unskilled workers lose more hours due to as their workplaces were more affected by lockdowns…

Working Hours
(% deviations from pre-pandemic levels)



…while consumption falls more for skilled workers with higher income.

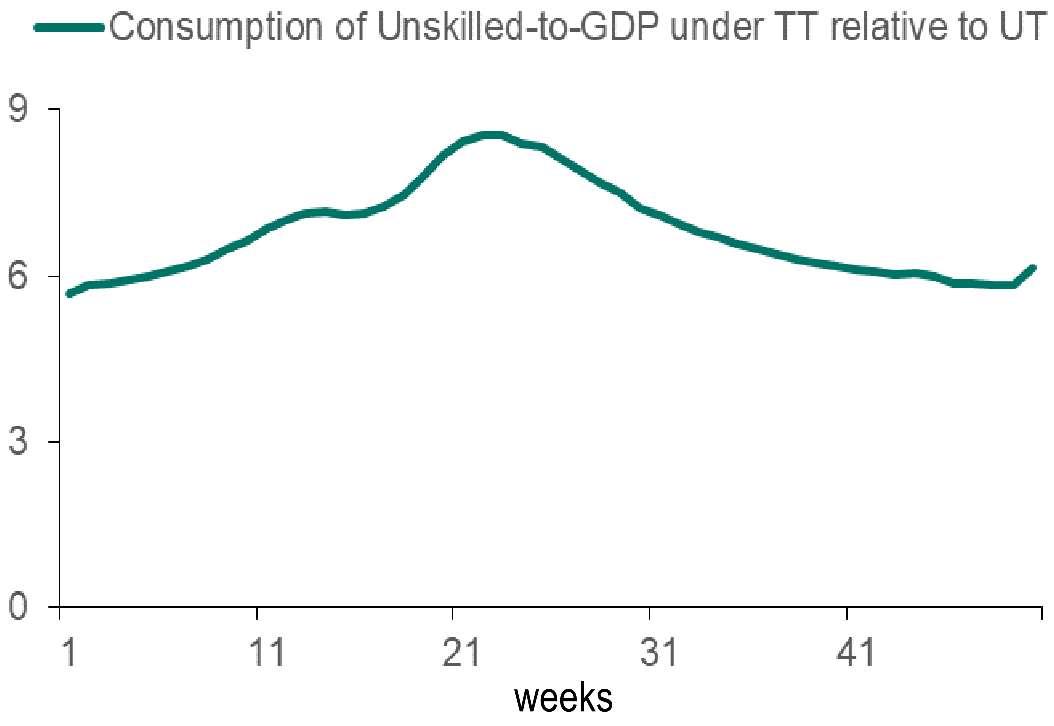
Consumption
(% deviations from pre-pandemic levels)

Source: Engler, Rodriguez, Pouokam, and Yakadina (2020)

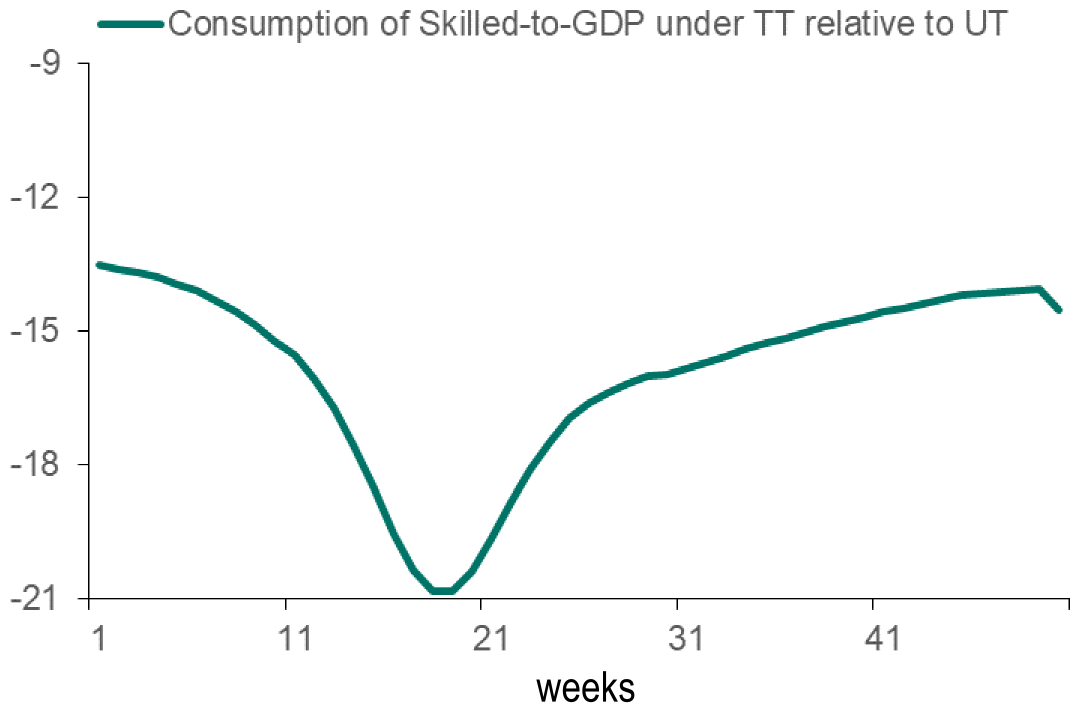
Model simulations:

Targeted versus Untargeted Fiscal Support
((Differences, percent of GDP or in % pts

Targeted support leads to higher consumption share of the unskilled in GDP ...



…... while the skilled experience a significant reduction in their consumption share because of redistributive measures

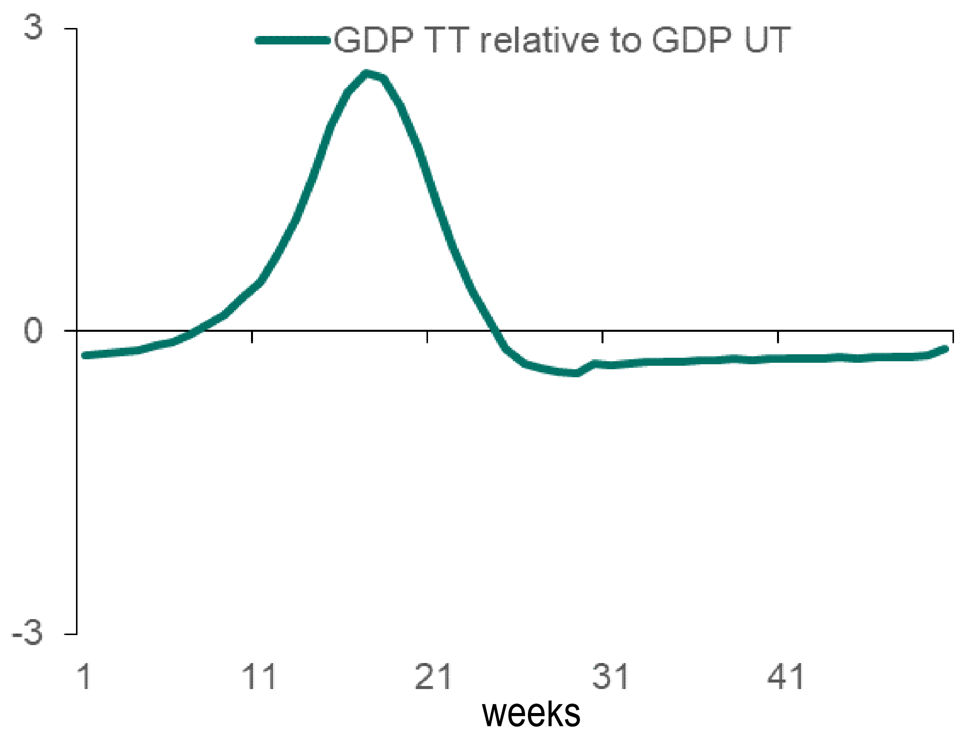


Source: Engler, Rodriguez, Pouokam, and Yakadina (2020)
Note: TT = targeted transfers; UT = untargeted transfers

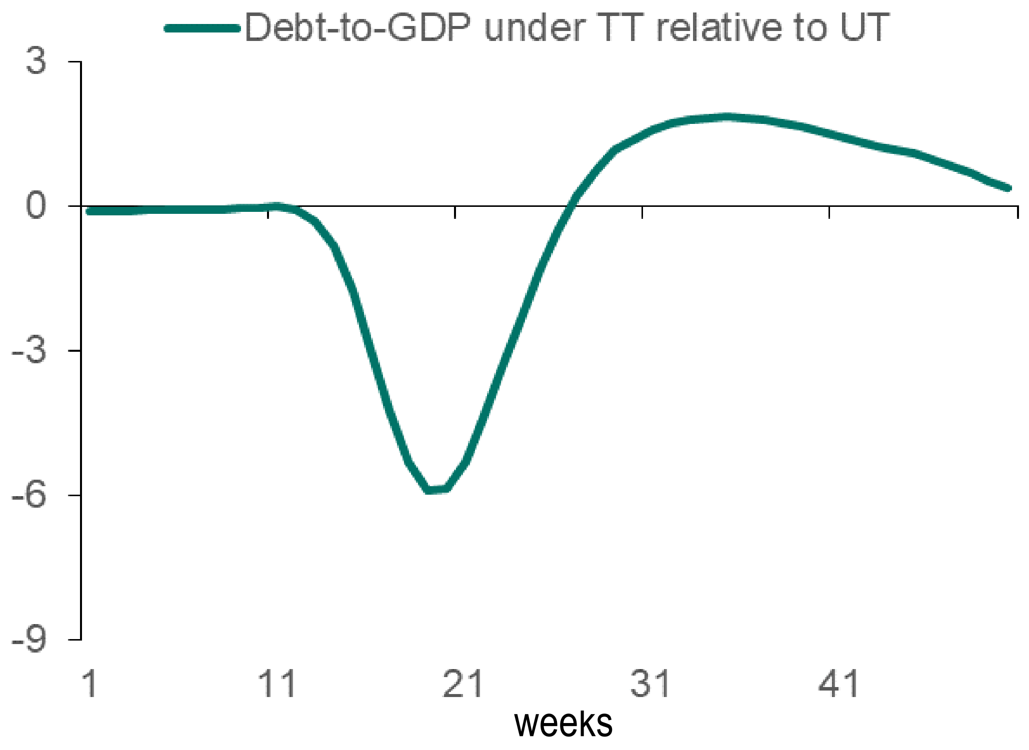
Model simulations:

Targeted versus Untargeted Fiscal Support
(Differences, percent of GDP or in % pts)

Optimal policy with targeted transfers results in a higher GDP relative to the one with untargeted transfers ...



...which leads to a lower pandemic debt accumulation...



Source: Engler, Rodriguez, Pouokam, and Yakadina (2020)
Note: TT = targeted transfers; UT = untargeted transfers

Thank you