Pandemics, Inequality, and Fiscal Policy

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Sources for presentation

Papers on: pandemics, inequality, austerity (CEPR, 2020, 21)

Book: Confronting Inequality (CUP, 2019)
Outline of the presentation

• Descriptive statistics on major epidemics from the past two decades

• The aggregate and distributional impact of pandemics
  – Baseline results
  – Robustness checks (sample; method; endogeneity i and ii; parallel trend)
  – Transmission channels (different measures of inequality)
  – Heterogeneity across episodes (case severity; output severity)

• The role of fiscal policy in mitigating the adverse effects of pandemics on inequality
So what Episodes Are We Talking About?

<table>
<thead>
<tr>
<th>Starting Year</th>
<th>Announced month</th>
<th>Event Name</th>
<th>Number of countries</th>
<th>Total Deaths</th>
<th>Total Cases</th>
<th>Total Mortality rate (%)</th>
<th>Average Cases/Pop (*100,000)</th>
<th>Average Mortality rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2003</td>
<td>2</td>
<td>SARS</td>
<td>27</td>
<td>774</td>
<td>8,094</td>
<td>9.56</td>
<td>1.25</td>
<td>9.77</td>
</tr>
<tr>
<td>2009</td>
<td>4</td>
<td>H1N1</td>
<td>149</td>
<td>19,091</td>
<td>6,502,779</td>
<td>0.29</td>
<td>122.69</td>
<td>4.02</td>
</tr>
<tr>
<td>2012</td>
<td>3</td>
<td>MERS</td>
<td>22</td>
<td>572</td>
<td>1,453</td>
<td>39.37</td>
<td>0.24</td>
<td>35.95</td>
</tr>
<tr>
<td>2014</td>
<td>8</td>
<td>Ebola</td>
<td>6</td>
<td>8,767</td>
<td>24,809</td>
<td>35.34</td>
<td>74.37</td>
<td>16.34</td>
</tr>
<tr>
<td>2016</td>
<td>2</td>
<td>Zika</td>
<td>21</td>
<td>20</td>
<td>198,122</td>
<td>0.01</td>
<td>76.21</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Total # of Episodes: 225

Sources: WHO, Ma, Rogers and Zhou (2020) Furceri and others (2020); ECDC, CDC; PAHO; Wikipedia. Data on population are from the World Bank’s World Development Indicator Database.
Historical Episodes: Regional Vs. Global

- **SARS**
  - Africa
  - Asia
  - Europe
  - North America
  - Oceania
  - South America
  - Cases/Population (*100,000)

- **H1N1**
  - Africa
  - Asia
  - Europe
  - North America
  - Oceania
  - South America
  - Cases/Population (*100,000)

- **MERS**
  - Africa
  - Asia
  - Europe
  - North America
  - Oceania
  - South America
  - Cases/Population (*100,000)

- **EBOLA**
  - Africa
  - Asia
  - Europe
  - North America
  - Oceania
  - South America
  - Cases/Population (*100,000)

- **ZIKA**
  - Africa
  - Asia
  - Europe
  - North America
  - Oceania
  - South America
  - Cases/Population (*100,000)
Two measures of the pandemic

1) (0,1) dummy variable: WHO declares a country to be affected by a particular pandemic

2) Continuous variable: cases relative to population

\[
\log(\text{cases}_{i,t}) = \log_{10} \left( 1 + \frac{1000 \cdot \text{confirmed_cases}_{i,t}}{\text{population}_{i,t}} \right)
\]
Empirical method

• Local projections (Jorda, 2005)

\[ y_{i,t+k} = \beta^k D_{i,t} + \theta^k X_{i,t} + \alpha_i^k + \gamma_t^k + \varepsilon_{i,t+k} \]

\[ y_{i,t+k} = \beta_c^k \log(cases_{i,t}) + \theta^k X_{i,t} + \alpha_i^k + \gamma_t^k + \varepsilon_{i,t+k} \]

• Impulse response functions

\[ IRF_{D}^{\text{dummy}} = E(y_{t+k}|pand_{epis}, t = 1; X_{i,t}) - E(y_{t+k}|pand_{epis}, t = 0; X_{i,t}). \]

\[ IRF_{\log(cases)}^{\text{dummy}} = E(y_{t+k}|\log(cases_{i,t}) = \zeta + 1; X_{i,t}) - E(y_{t+k}|\log(cases_{i,t}) = \zeta; X_{i,t}). \]
Impulse response functions are estimated using a sample of 179 countries over the period 1960-2019. The shaded area corresponds to 90% confidence bands. The dashed lines correspond to 68% confidence bands.

Impact of “average” pandemic ≈ 1 case per 1000 inhabitants
Pandemics Worsen inequality

(0,1) variable

Cases relative to population
(impact of “average” pandemic ≈ 1 case per 1000 inhabitants)

Impulse response functions are estimated using a sample of 177 countries over the period 1960-2019
Controls: two lags of the dependent variable; two lags of the pandemic dummy; the level of GDP, the level of GDP squared; population density; the share of population in urban area; the KOF index of trade globalization; and the KOF index of financial globalization.

ADL method, as in Romer and Romer (2010)
The measure of incidence of pandemics is $\log(\text{cases})$. The blue line shows OLS results (left scale) and the red solid line the IV results (right scale).

Our IV approach consists of interacting a time-varying global term and a constant country-specific term. The global term is a dummy variable that takes the value of 1 for all countries in the years of pandemics outbreaks. The country term is average temperature.
Inverse Probability Weighting Jordà & Taylor (2016 – EJ)

• Pandemics not fully exogenous events: related to pre-existing country characteristics:
  – First stage: Construct a predictive model for the likelihood of pandemics (0,1 variable) using various controls including the level of GDP, its growth rate, average country temperature, total health & other fiscal expenditures, mortality rate, etc.
  – Second stage: use the propensity scores obtained from the first-stage Probit models to run an augmented regression-adjusted estimation, denoted AIPW. The restricted model is the baseline LP. The unrestricted model allows the effect of the controls to vary across the treatment & control groups.
  – Bottom Line: Results on impact of inequality robust to this approach to gauging average treatment effect.
Placebo test: Are Pre-Pandemic Trends Same Treatment & Control Obs? “Yes”

The impulse responses for the placebo test attribute the values of our measure of the incidence of pandemics randomly across the whole sample.
Impulse response functions are estimated using a sample of 64 countries over the period 1981-2017. The charts show the response and 90 percent confidence bands.
The employment-to-population ratio of people with basic levels of education falls significantly after pandemics.

Impulse response functions are estimated using a sample of 76 countries over the period 1990-2017. The charts show the response and 90 percent confidence bands.
Informality and self-employment increase after pandemics

Impulse response functions are estimated using a sample of 158 (176) countries over the period 1950-2016 (1991-2019) for informality share (self-employed share). The shaded area corresponds to 90% confidence bands. The dashed lines correspond to 68% confidence bands.
Pandemics engender stronger inequality impacts than other recessions and financial crises

Impulse response functions are estimated using a sample of 177 countries over the period 1960-2019. The charts show the response and 90 percent confidence bands.
Severe pandemics (cases or recessionary impact) have much larger inequality impacts than mild pandemics.

Impulse response functions are estimated using a sample of 177 countries over the period 1960-2019. The charts show the response and 90 percent confidence bands. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + F(z_{it})[\beta_L^k D_{i,t} + \theta_L^k X_{i,t}] + (1 - F(z_{it}))[\beta_H^k D_{i,t} + \theta_H^k X_{i,t}] + \varepsilon_{i,t+k}$. $F(z_{it})$ is an indicator function of the severity of the pandemic.
Pandemics and inequality: role of the fiscal response

- Impact of pandemics on general government fiscal balance.
- Impact of pandemics on Debt-to-GDP ratio.
- Impact of pandemics on net Gini: the role of the fiscal response.
Following a pandemic, the fiscal balance weakens and the ratio of public debt-to-GDP increases.

(0,1) variable for incidence

Cases relative to population

(impact of “average” pandemic ≈ 1 case per 1000 inhabitants)

Impulse response functions are estimated using a sample of 185 countries over the period 1980-2019. The shaded area corresponds to 90% confidence bands. The dashed lines correspond to 68% confidence bands.
Empirical method

• Methods
  – Smooth transition

\[ y_{i,t+k} = \alpha_i^k + \gamma_t^k + F(z_{it})[\beta^k L D_{i,t}] + (1 - F(z_{it}))[\beta^k H D_{i,t}] + \theta^k L X_{i,t} + \epsilon_{i,t+k} \]

with \( F(z_{it}) = \frac{\exp^{-\gamma z_{it}}}{(1 + \exp^{-\gamma z_{it}})}, \quad \gamma = 1.5 \)

• Cyclical adjustment of fiscal variables

\[ z_{it} = \alpha_i + \beta_i \Delta y_{it} + \epsilon_{it} \]
Supportive Fiscal Balance Mitigates Pandemic’s Impact on Inequality

The shaded area corresponds to 90% confidence bands. The dashed lines correspond to 68% confidence bands.
Supportive Health Expenditures Mitigate the Pandemic’s Impact on Inequality

The shaded area corresponds to 90% confidence bands. The dashed lines correspond to 68% confidence bands.
Conclusions

• 21st century pandemics have led to persistent increases in Gini coefficient.

• Past pandemics raised the income share of higher-income deciles and lowered the employment-to-population ratio for those with basic education compared to those with higher education.

• The impact of past pandemics on inequality has been greater in the more severe episodes (cases or GDP)—augurs poorly for COVID-19’s impact.

• Austerity breeds K-shaped recoveries: the rise in inequality is higher when fiscal policy is tighter, while when the fiscal response is supportive, inequality barely increases.

• Key is for policy to remain supportive for the long haul.
Thank you