Responding to COVID-19 in Developing Countries

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Poor Countries Need to Think Twice About Social Distancing

Policies imposed in rich countries to fight the coronavirus could have adverse effects in low-income nations—potentially endangering more lives than they save.

BY AHMED MUBIRUQ MUBARAK, ZACHARY BARNETT-HOWELL | APRIL 9, 2020, 4:25 PM

In response to the coronavirus pandemic, varying levels of social distancing have been implemented around the world, including in China, Europe, and much of the United States. Hundreds of millions of people have accepted dramatic disruptions to their daily lives and substantial economic losses based on the reasoning that slowing the spread of the coronavirus can keep health care systems from becoming overwhelmed.

Epidemiological models make clear that the cost of not intervening in rich countries would be in the hundreds of thousands to millions dead, an outcome far worse than the deepest economic recession imaginable. In other words, social distancing interventions and aggressive suppression, even with their associated economic costs, are overwhelmingly justified in high-income societies.

But the logic of this response is built on the characteristics of the industrialized, relatively wealthy societies where the policy has emerged. Low- to middle-income countries, such as Bangladesh and Nigeria, are different and raise different questions, namely: Do the benefits of countrywide lockdowns also outweigh the associated economic costs in poor countries?

We see several reasons—including demographic composition, the source of people’s livelihoods, and institutional capacity—that suggest that the answer may be different than in the United States or Europe. To put it bluntly, imposing strict lockdowns in poor countries—where people often depend on daily hands-
Developing countries may not be best suited for strict social distancing

Very Different Population Distributions

17.4% of the population in HIC is elderly vs only 3% in LMICs

Flattening the curve unlikely to release pressure from health systems in LMICs

Delaying infections only useful if we can prevent the health system from getting overwhelmed. Not very valuable if health system capacity is extremely low or non-existent

Figure 5: Hospital and ICU demand in Bangladesh and the U.S.
Relative concerns about disease risk vs economic livelihoods very different in LMICs than in HICs

Day-wage laborers, migrants, agricultural workers in South Asia now facing food insecurity

80% of survey respondents concerned about income shocks and food security

66% decrease in hours worked between Jan and Apr 2020

Food insecurity increased substantially

65% reported that they were worried about enough food
http://yrise.yale.edu/covid-19
Social distancing is costly in poor countries

**Income shocks**
- >80% of workers in LMICs are informally employed
- No wage/employment guarantees

**Food Insecurity**
- Lockdowns can disrupt internal food supply chains, halt production, and increase prices

**Health Impact**
- Lockdowns lower institutional births, pre-natal visits
- Vaccination delays for polio, tuberculosis, measles
- Malaria deaths in SSA could double due to program disruptions

**Learning Shocks**
- Indefinite school closures will lead to adverse learning outcomes

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Policy Priorities

**Social Protection Policies**

- Regardless of distancing policies, need to get money to the poor quickly
- How do we target the poor and get cash/food to them safely and effectively

**Sensibly Target Distancing Policies**

- Enforce bans on religious and social gatherings
- People only allowed out for economic livelihood
- Enforce universal mask wearing norms
- Enlist families to protect young and vulnerable

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**Policy Priorities**

**Behavior Change**

- Enlist community leaders to endorse and enforce policies
- Deploy frugal innovations like Ghanaian Veronica Buckets
- Enlist support of mobile services to collect data, deliver messages, deploy social influence strategies

**Data Collection**

- Collect data on symptoms, food security, and prices to spatially target support
Macroeconomic Policies

Need to send payments but these are not “stimulus payments”

- Payments to keep people at home, not stimulate economy
- Can we label transfers as “stay at home” to impose “soft” conditionality?

Target support to SMEs

- Protect SMEs to prevent irreparable damage to economy
- Target sectors the poor depend on, and firms which will have difficulty surviving
- e.g. you can buy an iphone later, but cannot have today’s restaurant meal later
Evidence-Based Policy Support in Bangladesh, Nigeria, Sierra Leone, Nepal

**High Frequency Data Collection**
- Symptom prevalence
- Public health behavior & knowledge
- Income shock, food insecurity
- Risk Exposure - migrants

**Migration Data to Identify Hotspots**
- Migrants as Disease Vectors
- Identify districts and upazilas at risk
- Losses in remittance revenues
- International transmission risk

**Info Campaigns & Social Influence**
- Personal appeals - social networks
- Community leaders (imams, teachers)
- A/B testing – incentives, identity, messaging content
- Scale effective strategies via govt, telcos

**Econ-Epi Modeling**
- Add economic and behavioral factors to epidemiological models
- Discipline with country data
- Provide specific policy guidance for LMICs

**Specific Sectors & Interventions**
- Produce and distribute masks
- Effects of prior cash distribution
- Protecting rice harvest & mill workers
- RMG Sector - Survey managers

**Targeting of Social Protection**
- How should we target cash transfers?
- How do we identify beneficiaries?
- Combine telecom records with detailed survey data
- Use machine learning

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Data Collection to Guide Policy

Collect data on:

- Symptoms
- Disease awareness
- Behavior and disease exposure
- Economic impact and food security

- Use symptoms data to estimate changing prevalence in the country over time and identify clusters where the disease might be growing. This could enable us to recommend more targeted isolation policies instead of a blanket lockdown.

- Understand the level of disease awareness in the community and identify the information gaps that may need to be filled and the behavioural patterns that need to be changed to promote disease prevention.

- Understand the magnitude of income shock and food insecurities faced by households to capture the economic cost of social distancing.

Map showing geographical coverage of two of our existing survey populations.

- [Link](http://yrise.yale.edu/covid-19/)
Improving Agricultural Extensions

Alleviating Seasonal Poverty

Y-RISE Strategy to Promote Behavior Change: Randomize roll out of multiple messaging strategies that raise COVID-19 awareness, test their effectiveness during data collection, and work with A2i to scale up the messaging channels that create highest impact.

We will raise awareness by running information treatments both at the household and community level. Evidence suggests that individual messages from acquaintances and community leaders are more effective than impersonalized text messages in changing behavior and at times of crises such as these, information is particularly effective when it comes from influential leaders in the community.

Household Level

- We will use a combination of social network, monetary incentives, and varying message content to raise awareness about COVID-19.
- Follow up surveys and real time epidemiological modeling will help us identify the most effective messaging strategies that can then be scaled.

Community Level

- In collaboration with A2i, BRAC, and Youth Policy Forum, we have mobilized 50+ volunteers to reach out to imams, headmasters, and health workers across 50 unions in Bangladesh.
- Over the next 10-14 days we will reach out to leaders in random geographical order.
- Ongoing phone surveys will help us capture the impact of reaching out to community leaders.
Executive Summary of migration-COVID links evident in the data

- Remittances of migrant workers are an important source of income for households in South Asia
- Migrant sending households have experienced sharper declines in income
- Migrant returnee presence in the community is associated with COVID-19 symptoms
- Returning migrants face stigma but the impact cannot (yet) be systematically evaluated

Policy Implication

WB estimates a 22% drop in remittances in South Asia
Bangladesh only collected 1.08 billion USD in April 2020, a 25% drop from last year
Households with return migrants worst hit by the pandemic
Ensuring that households that rely on remittances meet their basic need should be a priority

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Remittance income declined for migrant-sending households in Nepal & Bangladesh

**Bangladesh**
- Winners of visa lottery to Malaysia, indicative of high migration, earned 18-100% more 2013-2019, but 36% less in April, 2020

**Nepal**
- Households in Western Terai received an average of 4900 NPR in late 2019
- This fell to 1,700 NPR last month
Both because migrants were forced to return...

**Observed trends:**

- Returnees
  - Because many migrants were forced to return
  - Both from India and from cities in Nepal

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…and also because those still away are sending less money back

Observed trends:

Remittances also drop

- Migrants still away are also sending less money back home
- Drops from ~Rs. 3900 to Rs. 1200

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EXECUTIVE SUMMARY

Inadequate COVID-19 testing capabilities is producing testing data that cannot be reliably compared across countries or across jurisdictions within low- and middle-income countries (LMICs). This is hampering the ability of LMICs to devise timely and effective policy responses, such as identifying hotspots and spatially targeting public health responses or economic relief. Data deficiencies also hamper global resource allocation. International bodies such as the World Health Organization need comparative information on disease risk across countries, to be able to direct support to regions at greater risk.

We develop a methodology to make indirect inferences about the spatial distribution of COVID-19 risk using the migration destination. We construct an index of COVID-19 risk exposure for every country, using the number of emigrants from that country to COVID-affected destinations to infer the likelihood that return migrants are now bringing back the disease to each ‘home’ country.

2. We validate this COVID-19 exposure index by comparing it to the number of confirmed COVID-19 cases through testing, as well as to the number of COVID-deaths (given the aforementioned limitation of testing data). There are strong positive correlations between our index and both confirmed cases and deaths, in the order of +0.66 to +0.72. The strong predictive power of our index supports even
Migration links to COVID-affected destinations match well with recorded cases

Distress calls coming from various Bangladeshi districts match well with airport returnees Jan-March from COVID-affected destinations
Returnee Presence is associated with COVID-19 symptoms

- Strong correlation between returning migrants and self-reported common COVID-19 symptoms
- In both Cox’s Bazar and visa lottery samples, likelihood of reporting symptoms at least doubles for households reporting a returning migrant
Introduction: Targeting Relief Payment

SUMMARY: Combining “big data” (e.g. mobile phone records, satellite images) with pre-existing household survey data can improve targeting of relief payments quickly and at low cost.

The government may wish to target the following populations for benefit transfers:
- Poor and ultra-poor
- Most economically affected (most likely to have lost employment and income during the COVID crisis)
- Those whose livelihoods depend on mobility (such as migrant laborers, who are most likely to transmit disease if not conforming to lockdown)

The procedure we are pursuing in Bangladesh:
1. Collected survey data to identify households that meet some eligibility criteria for relief payment
2. Develop a statistical model that matches those eligible beneficiaries to mobile phone usage patterns (e.g. frequency of top-ups, amounts, mobility).
3. Develop a machine learning algorithm to identify eligible people based on phone usage patterns
4. Deploy this algorithm on the mobile phone records of the entire population
5. Add human elements (e.g. SMS texts, physical verification) to refine method

Need to decide on transfer modalities:
- Add any conditionality?
- Optimal amounts and frequency of transfers?
How do we do it? Overview of Method

Step 0: Create a labeled training set
- For a subset of subscribers, match CDR to survey data
- Goal is to find optimal \( f: \ Wealth_i = f(CDR_i) \)

Step 1: “Feature Engineering”
- Convert CDR into feature vectors
  - A: Traditional “intuitive” approach (performs poorly)
  - B: Deterministic Finite Automata (performs well)
  - C: Graph Convolutional Network (performs great)

Step 2: Supervised Learning / Modeling
- Train cross-validated & regularized model on labeled training set

Step 3: Validation
- Validate out-of-sample predictions using independently-collected data
Step 0: Labeled training set

Rwanda
- Geographically stratified random sample of 900 active subscribers
- Single-round survey
- Focus on “wealth index”
  - PCA of 12 different asset questions

Afghanistan
- 1,200 households in two districts
- High-frequency panel survey (13 rounds)
- Many more measures of welfare
  - Wealth index
  - Financial health
  - Vulnerability and shocks
  - Subjective well-being
Step 1: Feature Engineering

How to convert raw data into “features”? 

Key point: We need to do this *algorithmically*, not *intuitively*.
Step 1: Feature Engineering (DFA)

Deterministic Finite Automata (DFA)

- Advantages: Intuitive, creates “interpretable” features

<table>
<thead>
<tr>
<th>Feature</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weighted average of all first-degree neighbor’s “Day of week (DoW) entropy” of outgoing SMS volume</td>
<td>0.376</td>
</tr>
<tr>
<td>Avg. of alter’s “Hour of Day (HoD) entropy”, outgoing SMS</td>
<td>0.371</td>
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<tr>
<td>Avg. of alter’s DoW entropy for incoming SMS</td>
<td>0.364</td>
</tr>
<tr>
<td>Avg. of alter’s HoD entropy for incoming SMS</td>
<td>0.356</td>
</tr>
<tr>
<td>Median of alter’s incoming call length, weekends only</td>
<td>0.354</td>
</tr>
<tr>
<td>Median of alter’s incoming call length, calls over 60s</td>
<td>0.351</td>
</tr>
<tr>
<td>Median of alter’s incoming call length, weekend evenings</td>
<td>0.338</td>
</tr>
</tbody>
</table>
**Step 2: Supervised learning**

<table>
<thead>
<tr>
<th>“Features” used in Model</th>
<th>Elastic Net</th>
<th>Random Forest</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$r$</td>
<td>$R^2$</td>
</tr>
<tr>
<td>Graph-Convolutional Network</td>
<td>0.72</td>
<td>0.52</td>
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<tr>
<td>Deterministic Finite Automata</td>
<td>0.68</td>
<td><strong>0.46</strong></td>
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<tr>
<td>“Intuitive” 5-feature model</td>
<td>0.43</td>
<td>0.18</td>
</tr>
<tr>
<td>Total phone expenditures</td>
<td>0.29</td>
<td><strong>0.08</strong></td>
</tr>
</tbody>
</table>

[Details]
Step 2: Supervised learning

*Important Note:* A model trained in one country cannot be used in another!
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Step 3: Validation

How do these phone-based maps compare to maps produced with household survey (DHS) data?

• Note: DHS data only representative at district level (n=30)
The Politics, Economics and Sociology of Implementation

- Key actors:
  - Mobile Network Operators (CDR Data and Implementation)
  - Economists (“Who should be Targeted?” | Design of CCT | Survey Data)
  - Machine Learning & CS Modelers (“How do we identify beneficiaries?”)
  - Central Government (Regulatory Permission for Data Sharing)
  - Mobile money or Local Government (“How do we distribute funds?”)

- Sensitivities
  - Each operator’s competitive positioning in the MNO market
  - Politics – Politicians would prefer to create their own list and distribute
  - Civil Society – Are women, vulnerable groups protected?
  - Citizens – Can we really trust this system?

- Solution in Bangladesh?
  - We deploy the system in stages: 50 sub-districts first.
  - Track people’s reactions. Effects on food security via phone surveys
  - Scale up in stages only if the results look promising.
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