

# Scaling Effective Causes: Cash transfers and AI/ML

# Who is GiveDirectly?

# GiveDirectly sends cash to those living in poverty with no strings attached

We're one of the **fastest-growing NGOs** focused on international issues

We're backed by **institutions, governments, corporates, and individuals** working to end poverty

**1.2M+** Recipients reached to date

**\$950M** Funds raised for recipients

**11** Countries in which we've operated

**19** Randomized controlled trials completed or ongoing



**USAID**

Google.org



IKEA Foundation



# Our approach

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Owning the end-to-end program enables us to **move quickly and efficiently** while **ensuring integrity** of the whole process.

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# GiveDirectly manages the design, execution and evaluation of unconditional cash transfer programs



# GiveDirectly goal is to accelerate the end of poverty through cash transfers

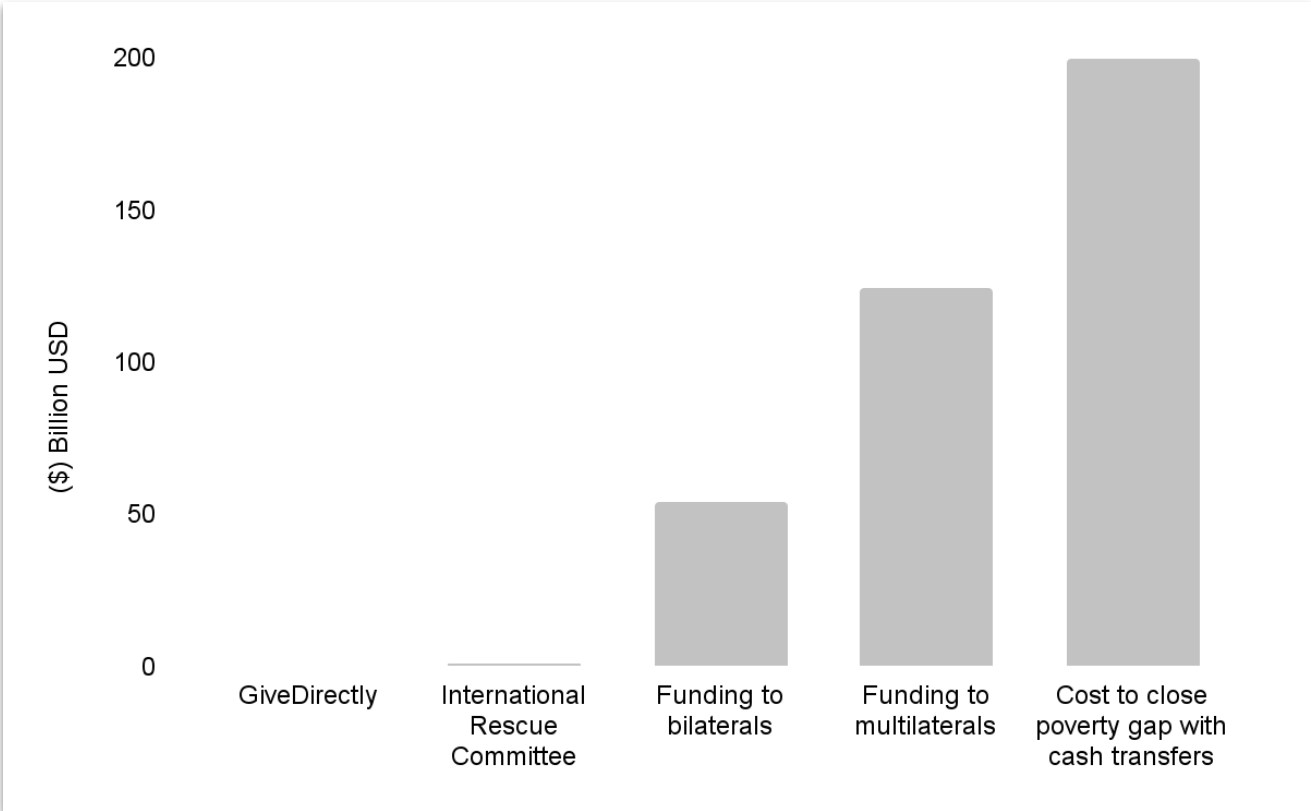
We're one of **fastest-growing NGOs**

**1.2M+** Recipients

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**11** Countries

**19** RCTs



# We need to deliver support with **scale, speed and accuracy**

## **Scale**

37M people have already slipped back into poverty  
- our response must be able to scale globally  
(674M)

## **Speed**

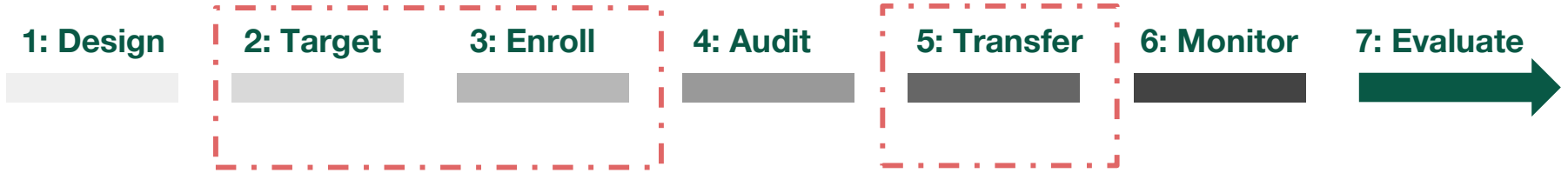
Families need help today.  
e.g. 72% of GD recipients in Kenya have  
<2 days savings.

## **Accuracy**

With limited resources, it's imperative we identify and prioritize those who most need aid

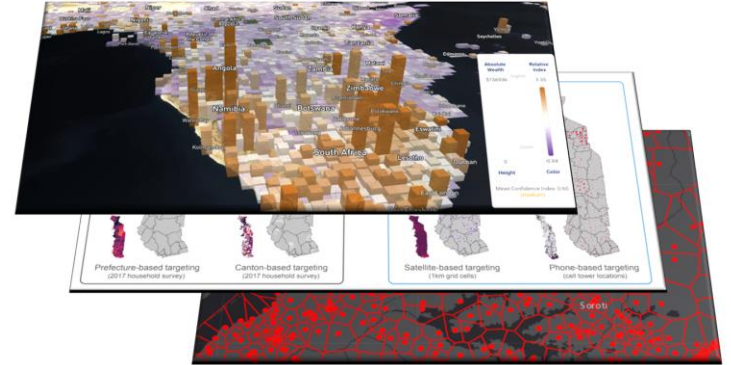


# What are the bottlenecks to **scale, speed, accuracy**?



## How do we define **good** targeting?

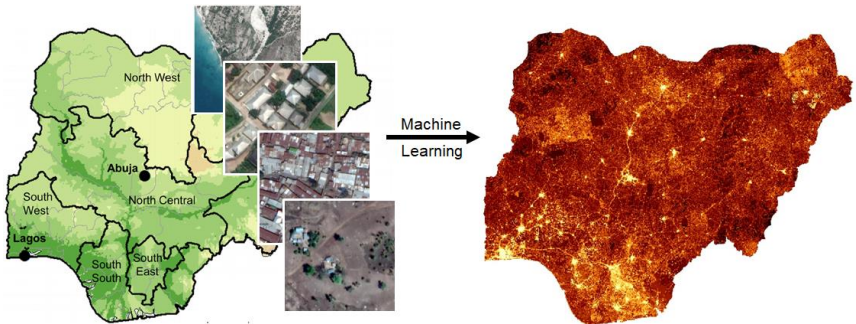
- **Inclusion** of the poor
- **Exclusion** of the non-poor
- **Efficient**
- **Fraud Resistant**



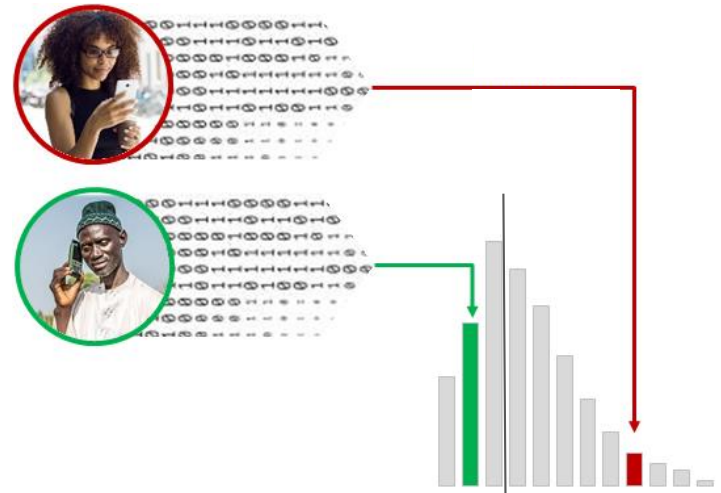
# Scaling cash transfer delivery: AI/ML and Togo

# In the midst of C-19 pandemic: Can we improve targeting with the latest in data science research?

Satellite imagery, processed with AI, can identify the **poorest neighborhoods** to prioritize for aid

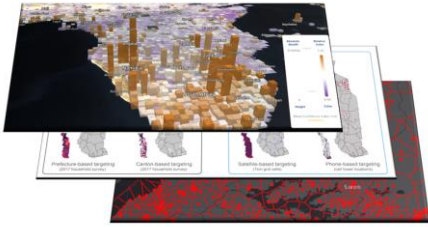


Mobile phone metadata can accurately **identify eligible beneficiaries**, using patterns of phone use



# How did the program - GiveDirect-Novissi - work? There were three steps

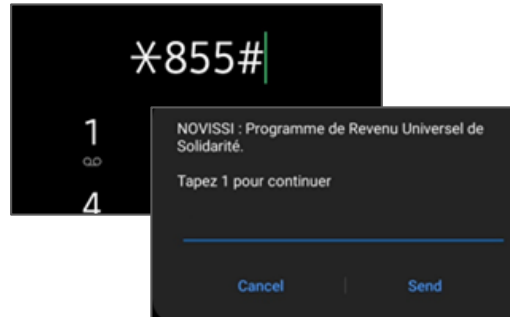
## Step 1. Pre-identify & target



- Find the poorest geographies using satellite prediction
- Identify poorest people in those geos based on cell usage patterns
- Whitelist cell phone numbers

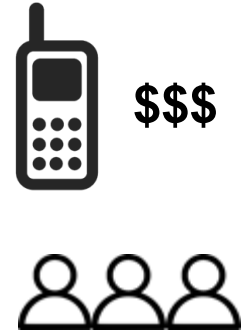
## Step 2. Self-Enroll

Recipient front end



- In poorest geos, launch radio ads **inviting families to dial \*855#**
- Applicant enters ID info
- On backend, **screen phone number and ID against whitelists**

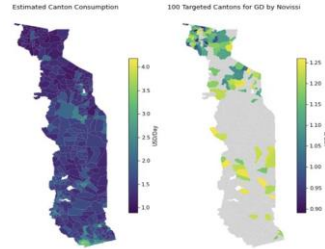
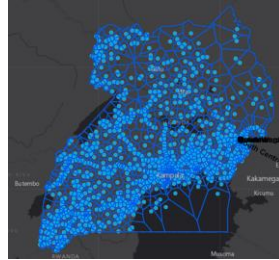
## Step 3. Pay



- Pay white listed individuals **instantly** via mobile money

# In partnership with U.C. Berkeley, we brought expertise & \$10M in funding to help the Gov. of Togo rapidly target and deliver cash to individuals in extreme poverty nationwide

Through **cross-sector partnership**, we built a program capable of fast scale-up.



## Togo Ministry of Digital Transformation:

Togo gov't had cash programming, existing management platforms and wanted to make platform more secure and integrate new targeting approaches

+

## GiveDirectly:

Brought operational expertise in cash delivery, targeting, call center, data/protection and ethics expertise from previous remote cash programs

+

## Berkeley's Data-Intensive

## Development Lab:

Deployed leading AI and machine learning research for creation of poverty targeting algorithm

+

## TED + Google.org +

**WB/IDA:** GiveDirectly raised >\$10M in private sector funding from TED Audacious challenge and to be deployed in Togo using this targeting approach. Google.org & WB/IDA supported research funding

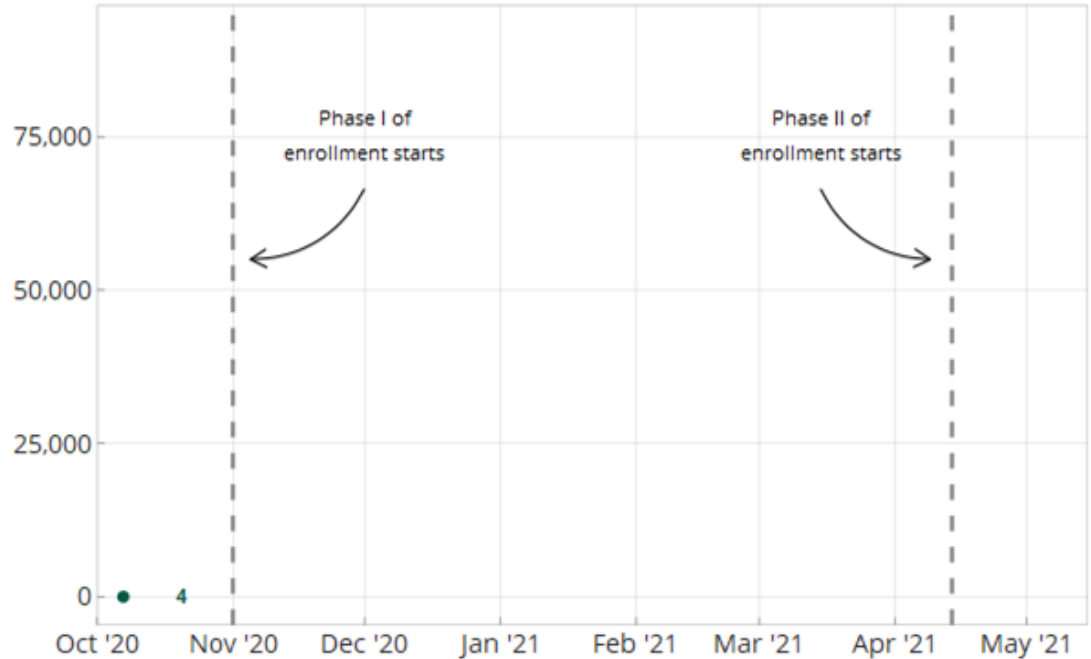
# Results: 140,000 individuals enrolled in the program in a matter of weeks

*“This project was foundational for us in terms of how we can set up our social protection system in Togo...”*

Shegun Bakari, Presidential Advisor  
Government of Togo

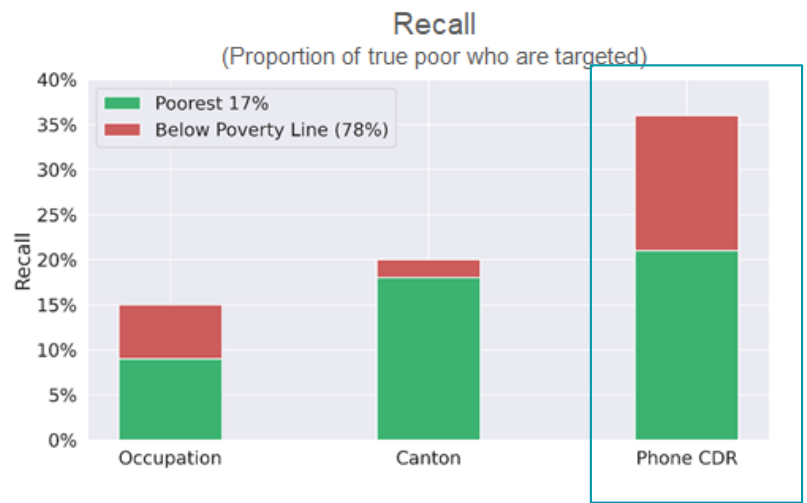
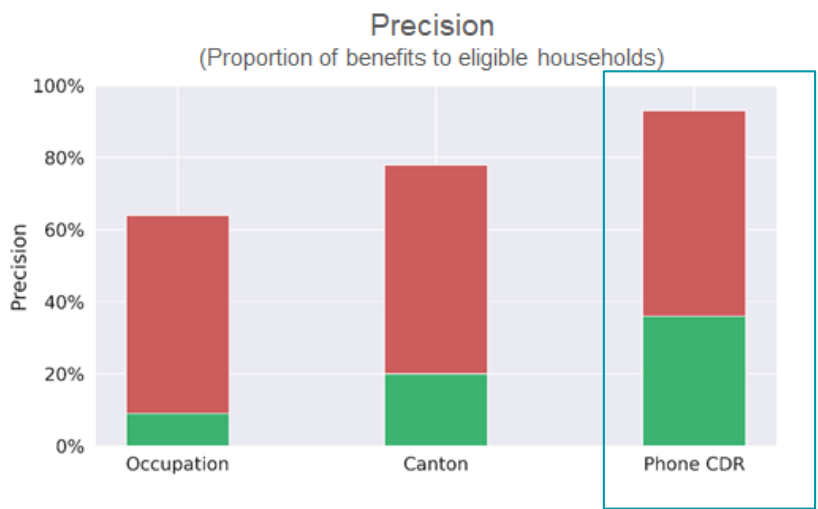


## Speed of cash delivery (# of beneficiaries)



# Research: using phone metadata was the most accurate targeting approach compared to other options

Phone-based targeting **was more accurate compared to the government's traditional targeting options** such as occupational or geographical based targeting



# Research: phone-based targeting was fair - it did not systematically exclude groups based on gender, ethnicity and other key demographics

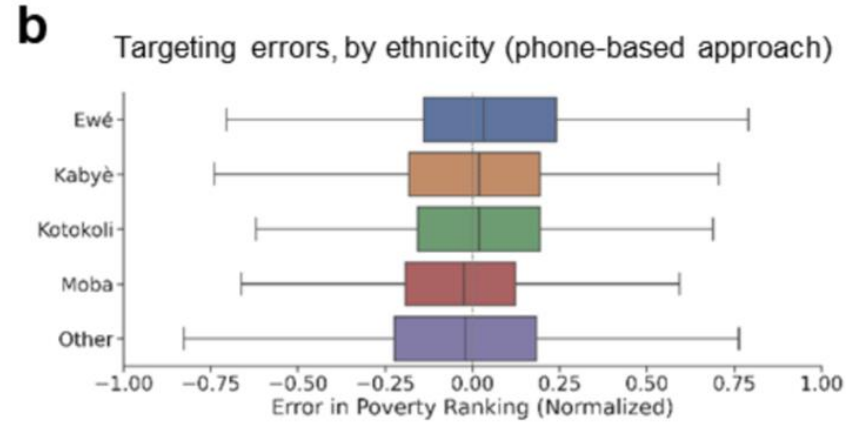
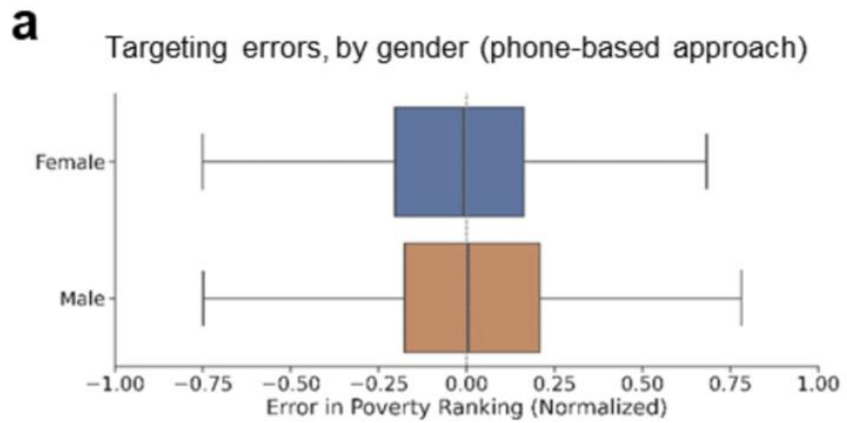


Figure 2 – Fairness of targeting for different demographic subgroups



The international journal of science / 31 March 2022

outlook  
Hepatitis B

# nature



## TELEPHONE CONNECTIONS

AI and mobile-phone data help target COVID aid more effectively

### Gas exchange

The race to turn carbon dioxide into useful products

### Supply and demand

Fix the way vaccines are rolled out before the next pandemic

### High tide

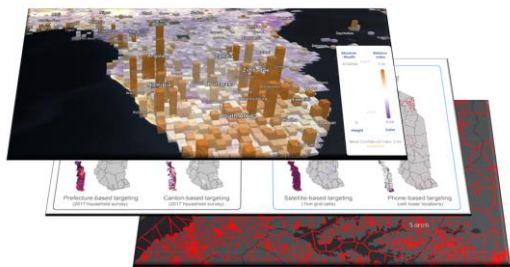
Increase in extreme storm surges linked to rising sea levels

Illustration: J. S. [unreadable]

**Where we go from here?**

# Beyond Togo: successfully scaled to the DRC, now we're expanding use cases / geographies

**2020** Piloted MobileAid in Togo



Used a machine learning-based targeting models to identify the poorest people in Togo

**2021** Expanded to DRC

**50,000**

Recipients paid total with 17,120 in first two days

**45 seconds**

The fastest recorded payment in GD's history

Provided technical support to Fonds Social to deploy "MobileAid" in Kinshasa

**2022 /2023**

Expand use cases



Apply MobileAid to large scale poverty alleviation, disaster responses, and social protection (Malawi, DRC Phase II, Bangladesh)

# Our Vision: Transform the delivery of cash globally

We are partnering with governments, telcos and regulators to position countries to **deliver cash to millions within minutes**



Develop **precision targeting technology**, based on cutting-edge data science research



**Set up automated enrollment and payment systems for delivering cash** to the poor/those impacted by crises, without meeting them in person



**Disseminate** open-source technology, rigorous evaluation and documentation

# Our Vision: Transform the delivery of cash globally

## Faster humanitarian response

- Mobile Aid + Anticipatory action
- MobileAid + rapid disaster response

## Large-scale poverty alleviation

- MobileAid + large scale programming
- Transitioning GiveDirectly programs to a MobileAid hybrid model

## Technical assistance and social protection

- Working with government partners to develop MobileAid capabilities in-house + integrate with social protection programs

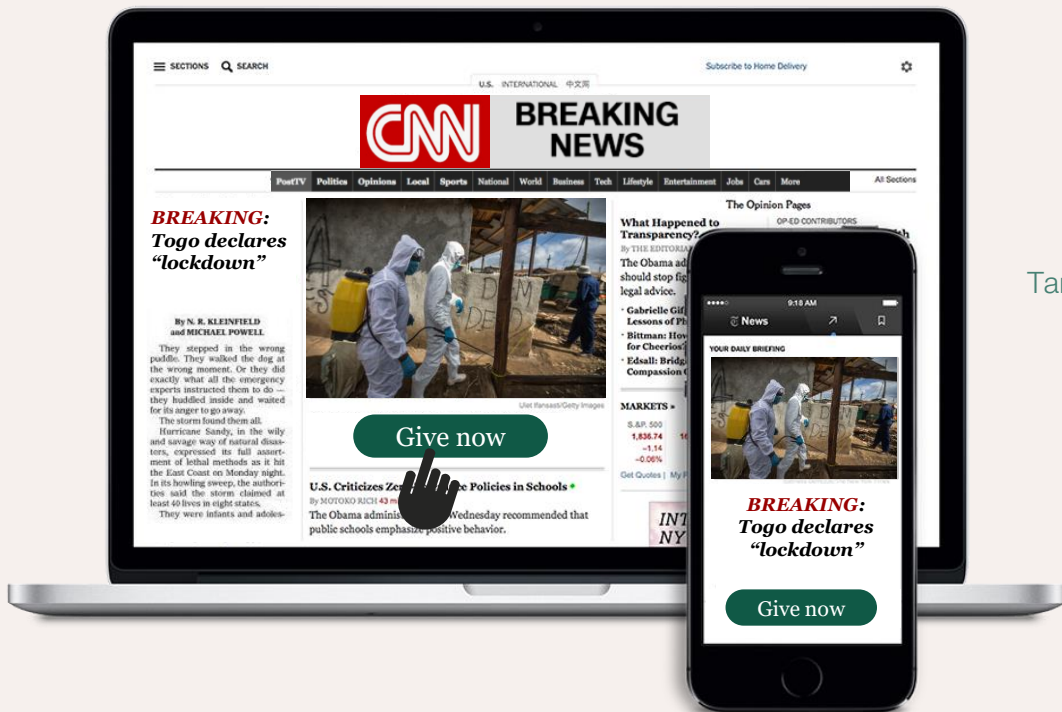


Government of Malawi



Setting up the digital infrastructure for remote targeting, enrollment and payments means that when a crisis hits...

...We can immediately send cash directly to those most affected



Target and send cash in minutes



**Want to learn more?**

# Interested in learning more?

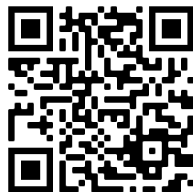
## Try out our new donation experience

Give money directly and learn about our programs using our new pre-enrolment donation experience



## Sign up for our newsletter

To stay up to date with our work, new project launches and giving opportunities



## Learn about our research studies

Rigorous, experimental evaluation is rare among nonprofits - read more on what we've done in this space





**We are hiring for high impact roles** → [GiveDirectly.org/jobs](https://GiveDirectly.org/jobs)

## Tech / Product

- Chief Technology Officer
- Director of Technical Program Management
- Software Engineers
- Senior Technical Program Manager

## Growth / Donors

- VP, Business Development
- Director of Major Giving
- Director of Principal Giving

## Field Operations

- Liberia Country Director
- Nigeria Country Director
- Regional Director
- Executive Director

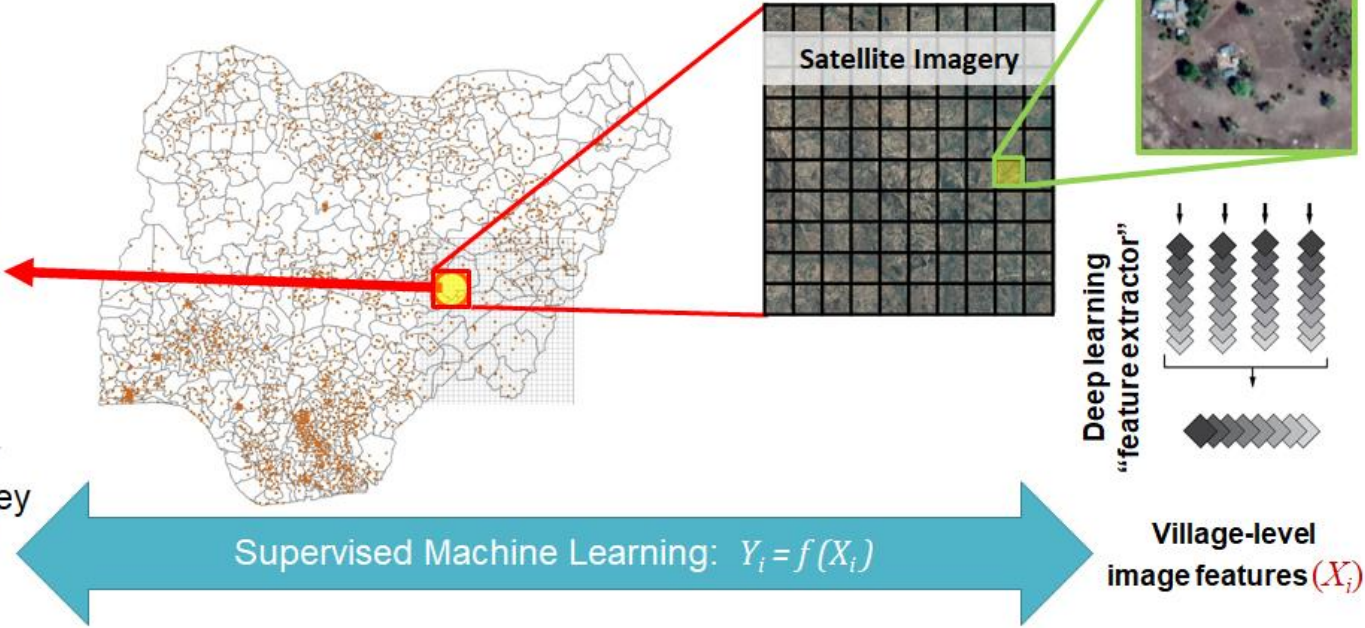
# Appendix

# Satellite-based poverty maps: How does it work?

- ML algorithms are trained using large, nationally-representative hh surveys
- Household locations are matched to “big” data from satellites and other sources

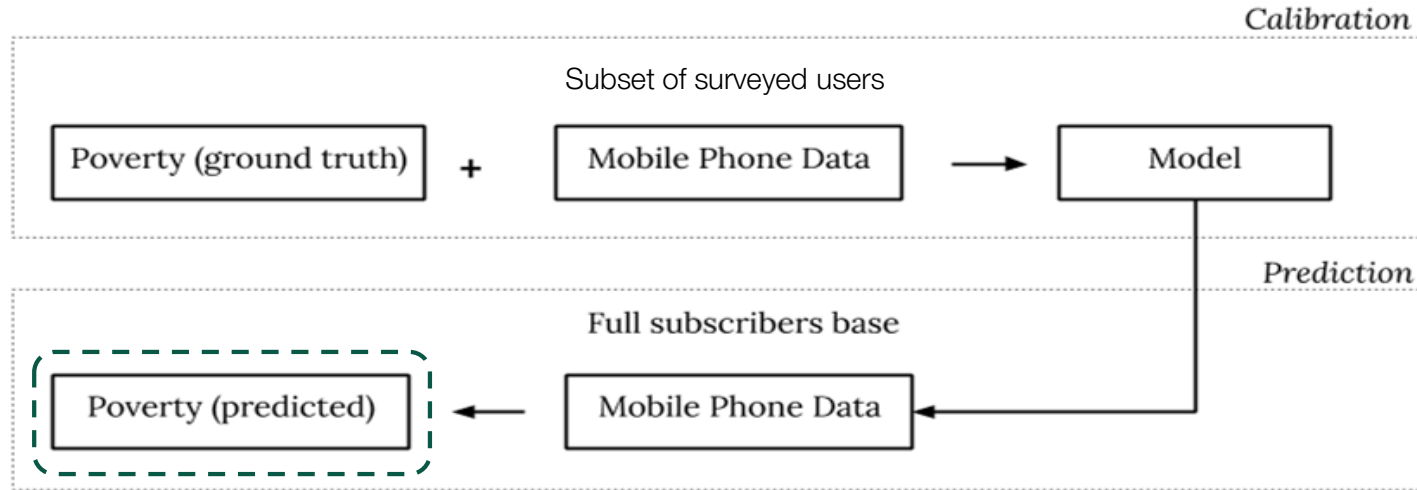


- 42,000 households
- 1,400 EA's
- ~35 households per cluster
- 100's of questions per survey
- Includes “wealth index” ( $Y_i$ )



Chi, G., Fang, H., Chatterjee, S., Blumenstock, J.E., 2020. “Micro-Estimates of Wealth for all Low- and Middle-Income Countries.”

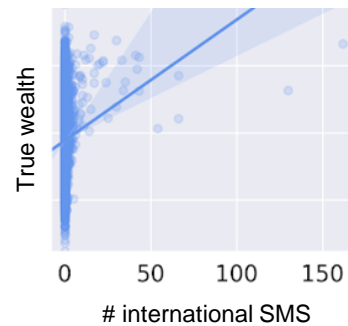
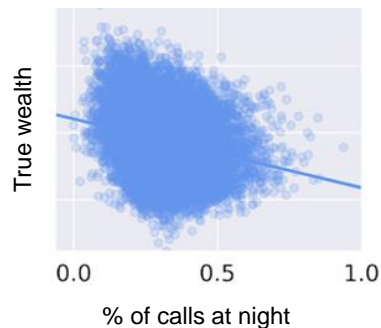
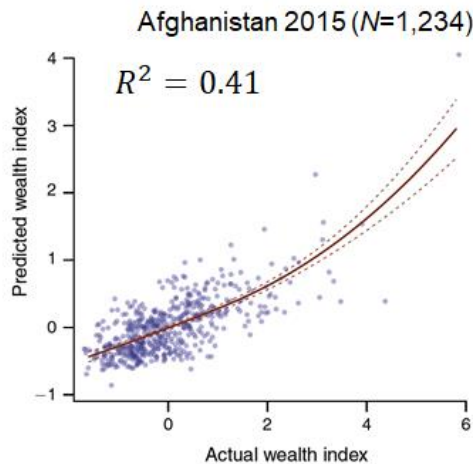
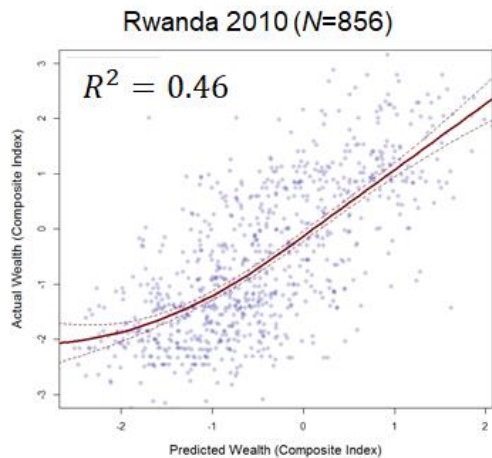
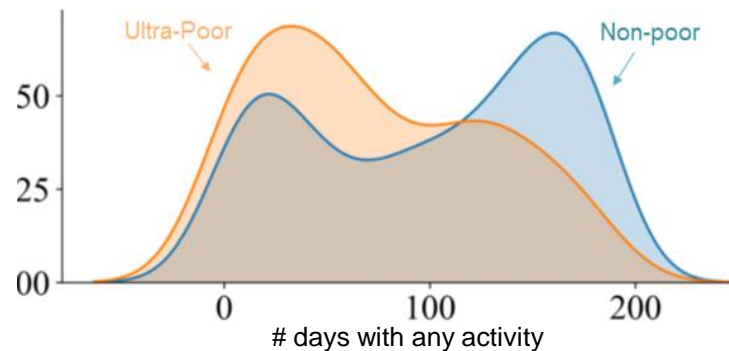
# Phone-based targeting: How does it work?



→ **End Result:** for each subscriber, predicted consumption or the probability of being eligible

# Phone-based targeting: How does it work?

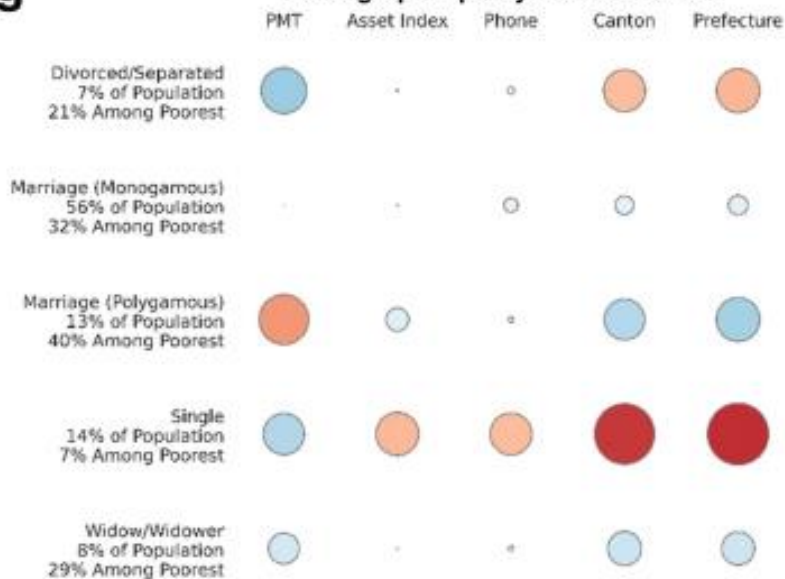
- Wealthy people use their phones differently from poor people
- ML algorithms, trained using surveys, identify these differences
- Across countries, CDR capture **40-50% of variation in wealth**



# Research: phone-based targeting was fair - it did not systematically exclude groups based on gender, ethnicity and other key demographics

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## Demographic parity: Marital status





\$25 ends my Coronavirus!

# GiveDirectly

*michael.kayemba@givedirectly.org*

[www.givedirectly.org](http://www.givedirectly.org) | [info@givedirectly.org](mailto:info@givedirectly.org)