

Targeting Development Aid with Machine Learning and Mobile Phone Data

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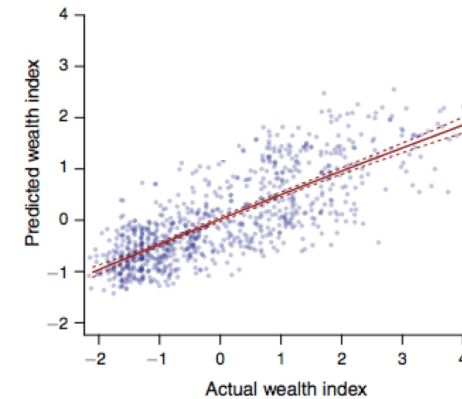
Motivation: Targeting

- Targeting the poor is key to cost-efficient anti-poverty programs (Hanna & Olken, 2018)
- Current methods are expensive (Alatas et al., 2012)...
 - Means tests, proxy-means tests, community wealth rankings
- ...and not always accurate (Coady et al., 2004; Brown et al. 2018)
- Could “digital trace data” be used to target development programs?
 - Mobile phone metadata most ubiquitous
 - Cost and time savings over traditional methods

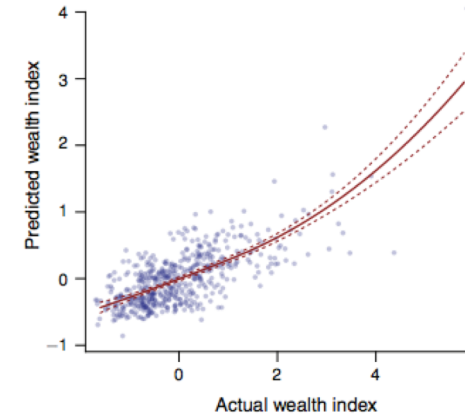
Past Work: Poverty Mapping

- Blumenstock, Cadamuro, & On (2015): Mobile phone metadata (CDR) is predictive of wealth in a sample of 856 geographically stratified individuals in Rwanda ($r^2 = 0.40$)
- Blumenstock (2018): Reproduces result in sample of 1,234 male heads of household in two districts of Afghanistan

Panel A. Rwanda model



Panel B. Afghan model



Source: Blumenstock (2018)

This Project

- Data from an anti-poverty program in Afghanistan
- **Question:** Can machine learning methods leveraging CDR data distinguish program-eligible “ultra-poor” households from ineligible households?
- **Short Answer:** Yes! CDR-based methods identify the ultra-poor as accurately as standard survey-based measures of wealth do.

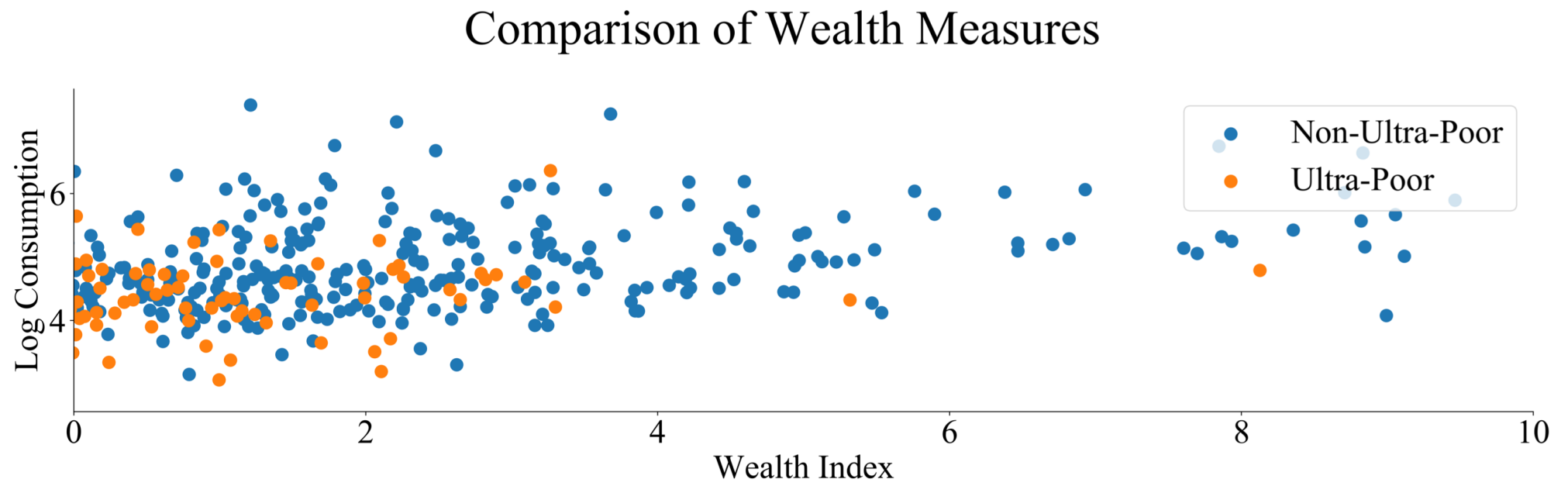
TUP Program

- Targeted ultra-poor households with “big push” intervention
- Targeting the ultra-poor: community wealth ranking followed by in-person verification
- World Bank RCT: 2,899 households
 - Asset-based wealth index
 - Consumption
 - **Ultra-poor indicator**



Source: sahareducation.org

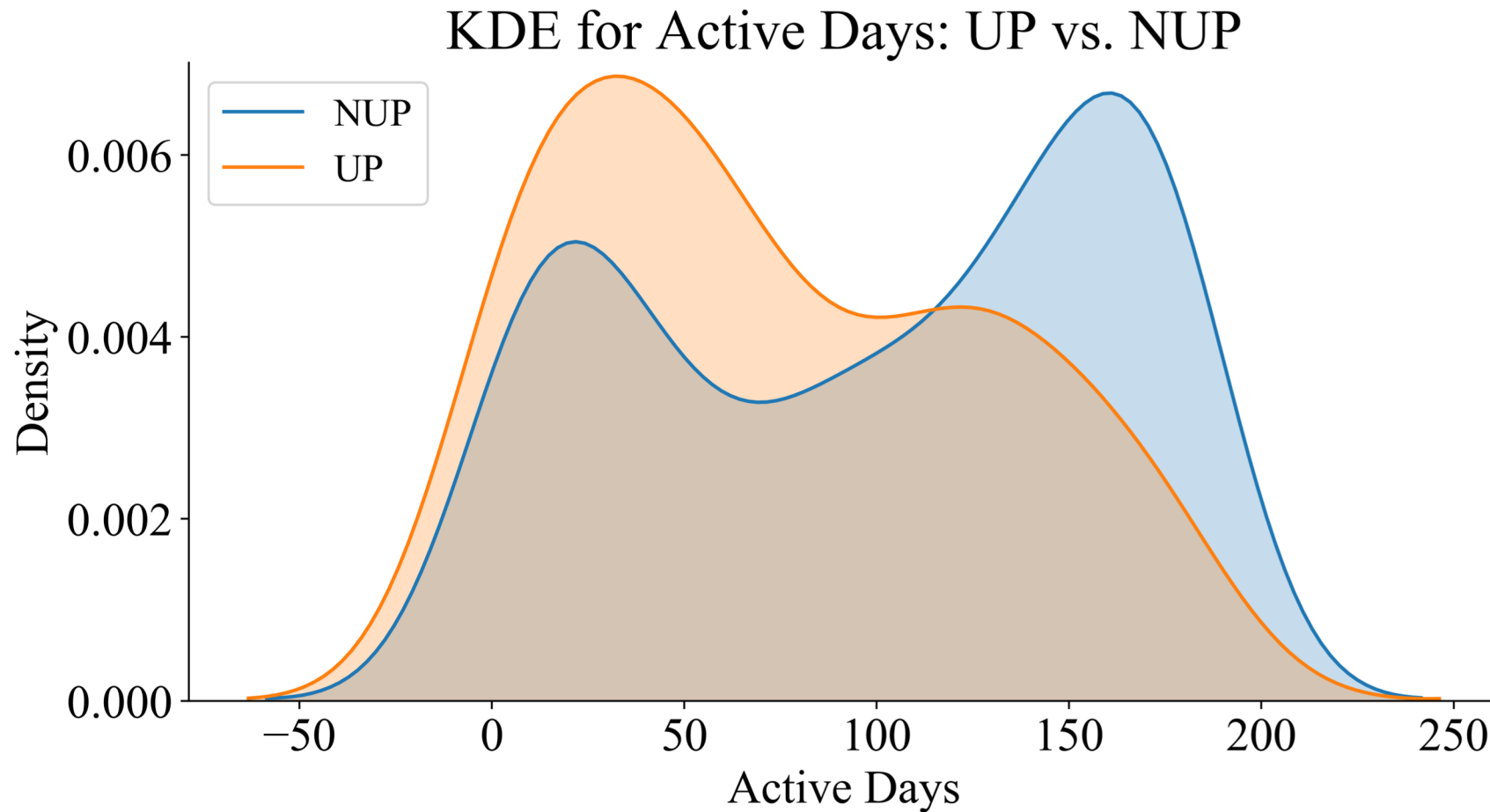
Comparison of Wealth Measures



Data Sources: CDR Data

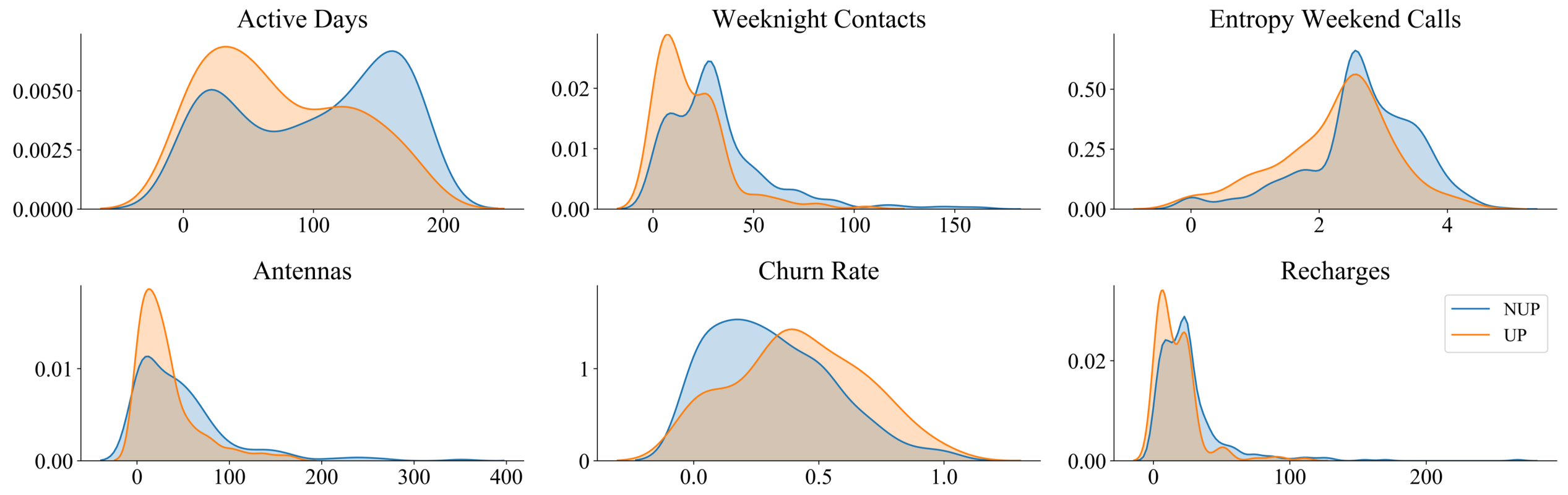
- Informed consent to match CDR to survey responses
- CDR from one of the largest Afghan cell providers
- 629,543 transactions for 537 households (27% UP) for November-April 2016
 - **Call:** Phone numbers for caller and receiver, time, duration, cell tower
 - **Text message:** Phone number for caller and receiver, time
 - **Recharge:** Time, amount
- 869 behavioral features extracted from CDR network data

Example CDR Features



Example CDR Features

Density of Selected CDR Features

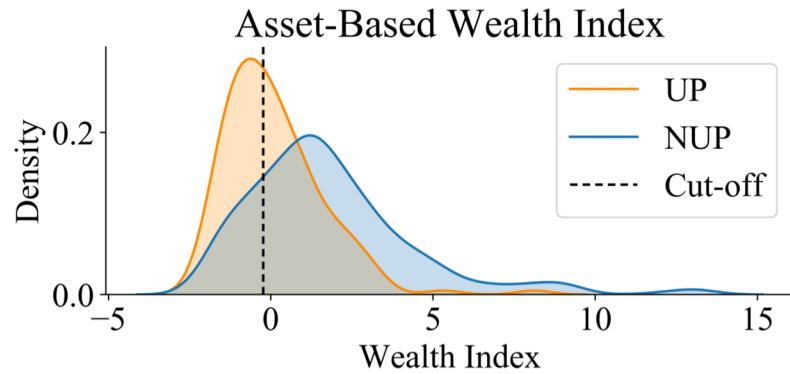


Targeting Methods

- Machine learning + CDR method: random forest
 - Cross-validation on training set to determine maximum depth
- Baseline methods: Asset-based wealth index, consumption
- Evaluation: Accuracy, errors of inclusion, errors of exclusion, ROC curve

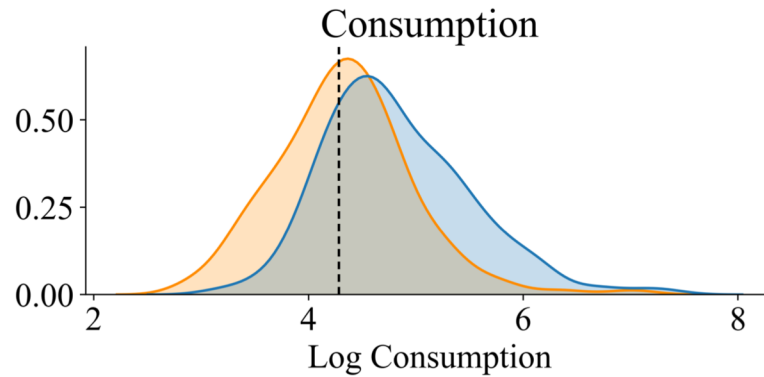
Classifying the Ultra-Poor

Confusion Matrices for CDR-Based Targeting vs. Standard Targeting Methods



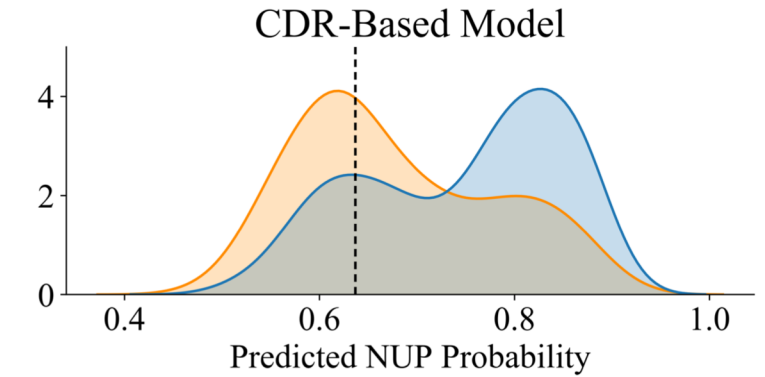
Confusion Matrix

NUP	316	75
UP	75	71
	Predicted: NUP	Predicted: UP



Confusion Matrix

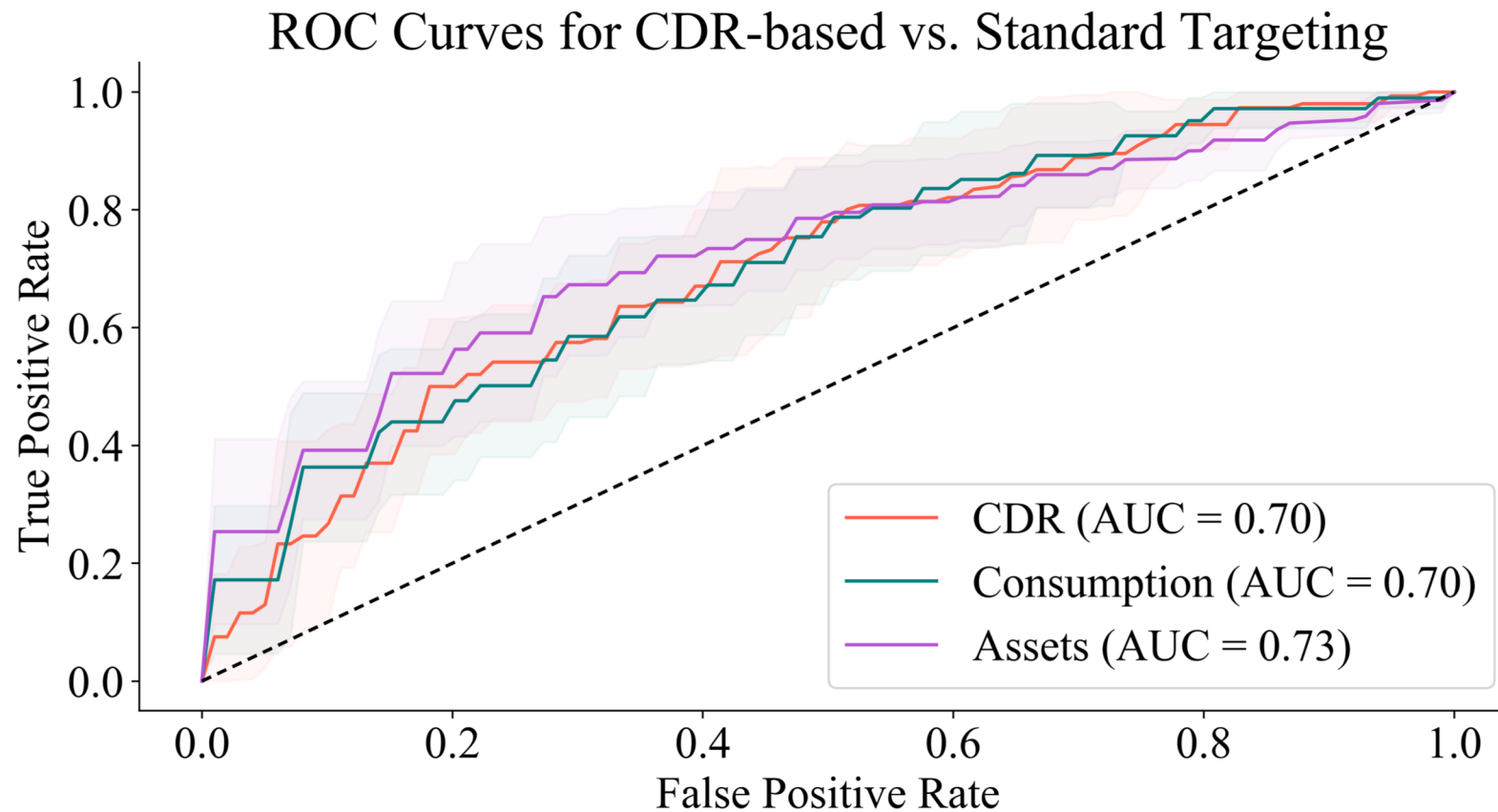
NUP	309	82
UP	82	64
	Predicted: NUP	Predicted: UP



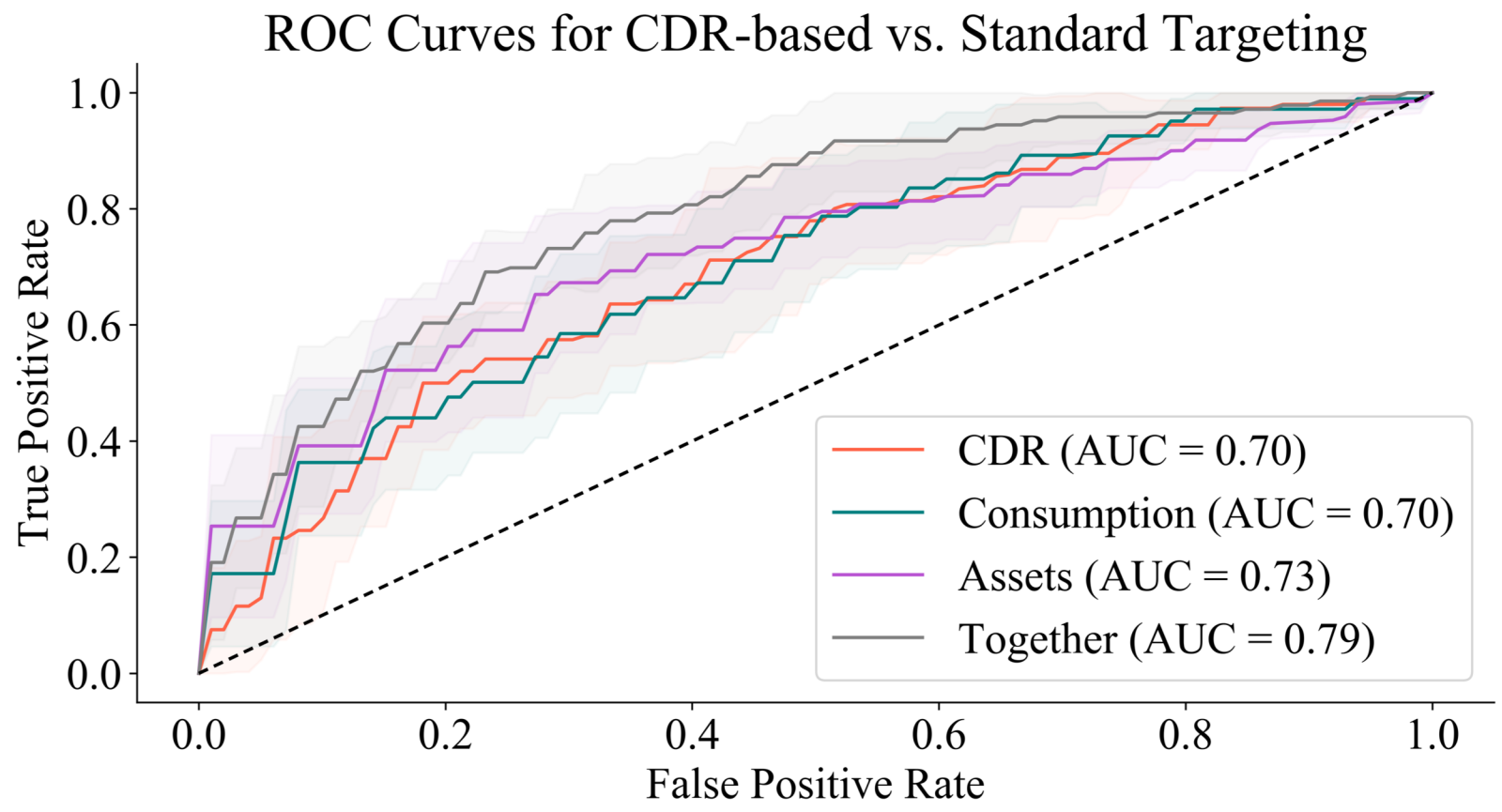
Confusion Matrix

NUP	312	79
UP	79	67
	Predicted: NUP	Predicted: UP

Classifying the Ultra-Poor



Combined Method



Concerns

- Phone ownership
 - More results here – see paper!
- Privacy
- Algorithmic transparency and interpretability (vs. system “game-ability”)
- Data sharing with mobile phone operators
- Technocracy

Summary

- For phone-owning households, CDR-based targeting methods are as accurate as consumption- and asset-based methods
- Combining CDR data with assets and consumption produces classifications more accurate than any single method
- Limitations
 - Non-phone-owning households
 - Other limitations of relying on digital trace data

Contact

- **Paper:** <https://tinyurl.com/cdr-targeting>
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Works Cited

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