Does Microfinance Still Hold Promise for Reaching the Poor? Facts and (A Little) Speculation

Robert Cull

March 17, 2015

The Promise (1)

"The hope is that much poverty can be eliminated – and that economic and social structures can be transformed fundamentally – by providing financial services to low-income households. These institutions, united under the banner of microfinance, share a commitment to serving clients that have been excluded from the formal banking sector."

Morduch, *Journal of Econ Lit*, 1999

The Promise (2)

"No one argues seriously that finance-based programs will be the answer for truly destitute households, but the promise remains that microfinance may be an important aid for households that are not destitute but still remain considerably below poverty lines."

Morduch, *Journal of Econ Lit*, 1999

The Critics

- Modest Benefits
- Over-indebtedness
- Commercialization, Less focus on serving the poor

Modest Benefits

- “We note a consistent pattern of modestly positive, but not transformative, effects…. The studies do not find clear evidence of reductions in poverty or substantial improvement in living standards.”

Banerjee, Karlan, Zinman
American Economic Journal: Applied Economics 7(1): 1-21, Jan 2015

- “These loans do help, but the changes are not transformative, certainly not transformative enough to justify charitable donations to the standard microcredit model.”

Esther Duflo, Innovations for Poverty Action (IPA) Press Release, 1/22/2015

Over-Indebtedness

“Microcredit markets are fragile. The poor have limited absorptive capacity for debt and can easily overextend themselves by taking on debt obligations in excess of what they can reasonably hope to service. While ambitious MFI outreach goals are to be applauded in principle, the reality is that overly zealous loan origination activities can override governance and control systems, leading to less rigorous credit standards and destructive, unintended consequences.”

Luis A. Viada (MicroRate) & Scott Gaul (MIX), *MicroBanking Bulletin, Feb 2012*

“The point is not to assert that we have a general problem with over-indebted microborrowers. The point is that for most markets we simply don’t know. We’re flying blind…

Richard Rosenberg, CGAP blog, January 2011

Over-indebtedness (2)

Some emerging research, but not our focus today

- Jessica Schicks, “Over-indebtedness in Microfinance – An Empirical Analysis of Related Factors on the Borrower Level.” *World Development,* 2014, 54: 301-324.
  - Survey of 531 microborrowers in Accra, Ghana
  - Over-Indebted if: (1) struggle to repay, (2) make (unacceptable) sacrifices to repay, (3) sacrifices are recurrent
  - Progress, but: self-reported, highlights difficulties in defining over-indebtedness, what’s the counter-factual?
- Adrian Gonzalez, MIX (now at World Bank), “Over-Indebtedness in Microcredit, CGAP blog, September 2011
  - Portfolio Quality Problems: Some Correlates
    - Market Saturation: Borrowers > 10% of population
    - Move toward formal: Salaried borrowers; non-microenterprise loans
    - Growth in already crowded markets

Commercialization: Compartamos vs. Yunus

- Compartamos: Small, uncollateralized loans, often to women, at high interest rates (~90% ann.)
  - April 2007 IPO, 30% of insiders' holdings
  - Oversubscribed by 13 times, Compartamos worth $1.6 billion
- Grameen Bank founder Muhammad Yunus, 2006 Nobel Peace Prize winner

"I am shocked by the news about the Compartamos IPO....When socially responsible investors and the general public learn what is going on at Compartamos, there will very likely be a backlash against microfinance."

Wrong turn?

[C]ommercialization has been a terrible wrong turn for microfinance, and it indicates a worrying 'mission drift' in the motivation of those lending to the poor."

- Muhammad Yunus, "Sacrificing Microcredit for Megaprofits," *New York Times,* January 14, 2011, p. A23

Talk Outline

I. Some Facts: Based on new (funding) data from the Microfinance Information eXchange (MIX)
II. A Commercial model: Greenfield MFIs and the IFC approach
III. Alternative MFI funding models and outcomes: The role of subsidy (More from the MIX) in reaching the poorest
IV. Alternative Delivery Channels: Reducing the costs of reaching the poorest

Part I: Some Facts on Microfinance Business Models

Based on work with

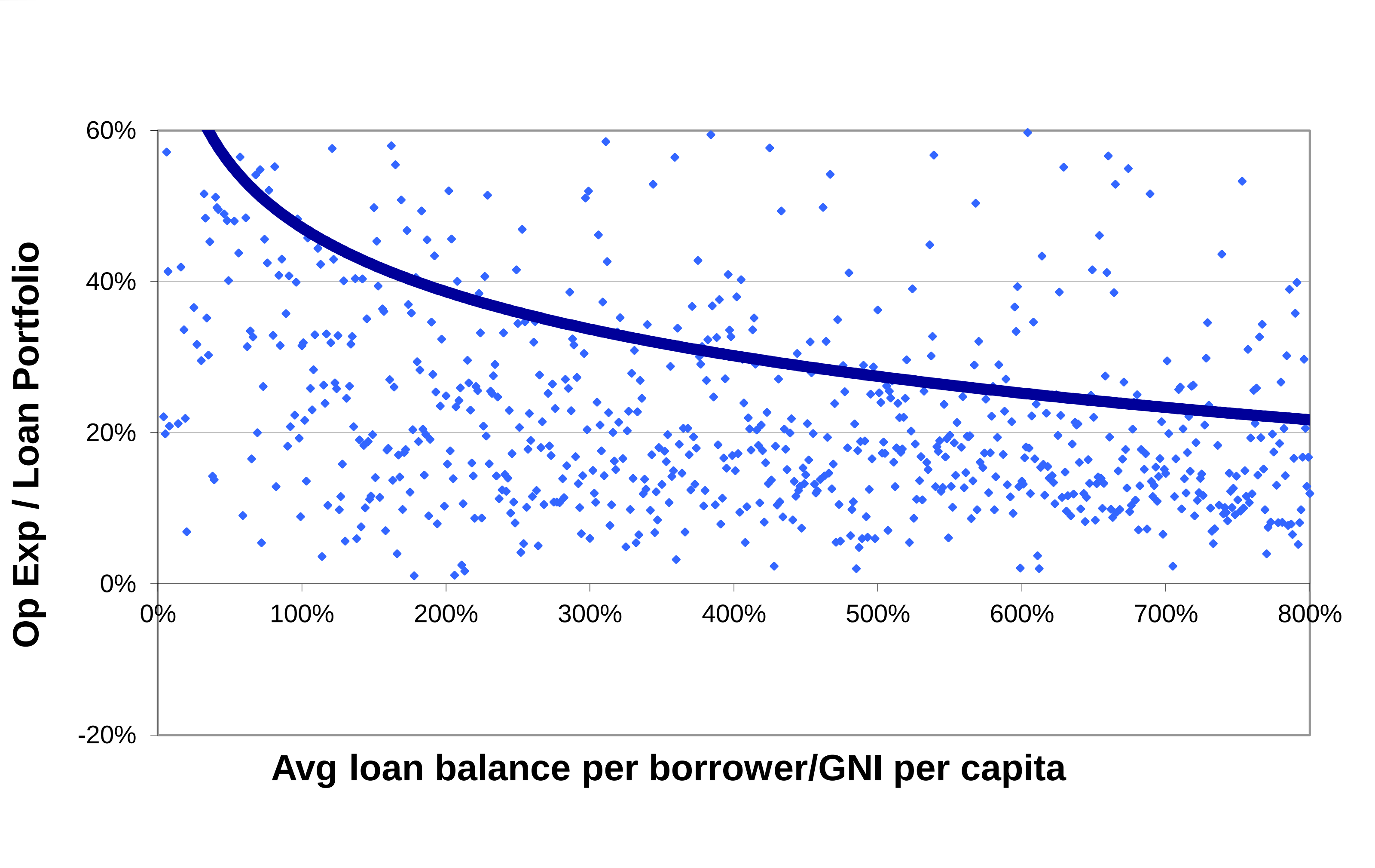
Asli Demirgüç-Kunt, World Bank
Jonathan Morduch, New York University

2005-2009 MIX Market Data

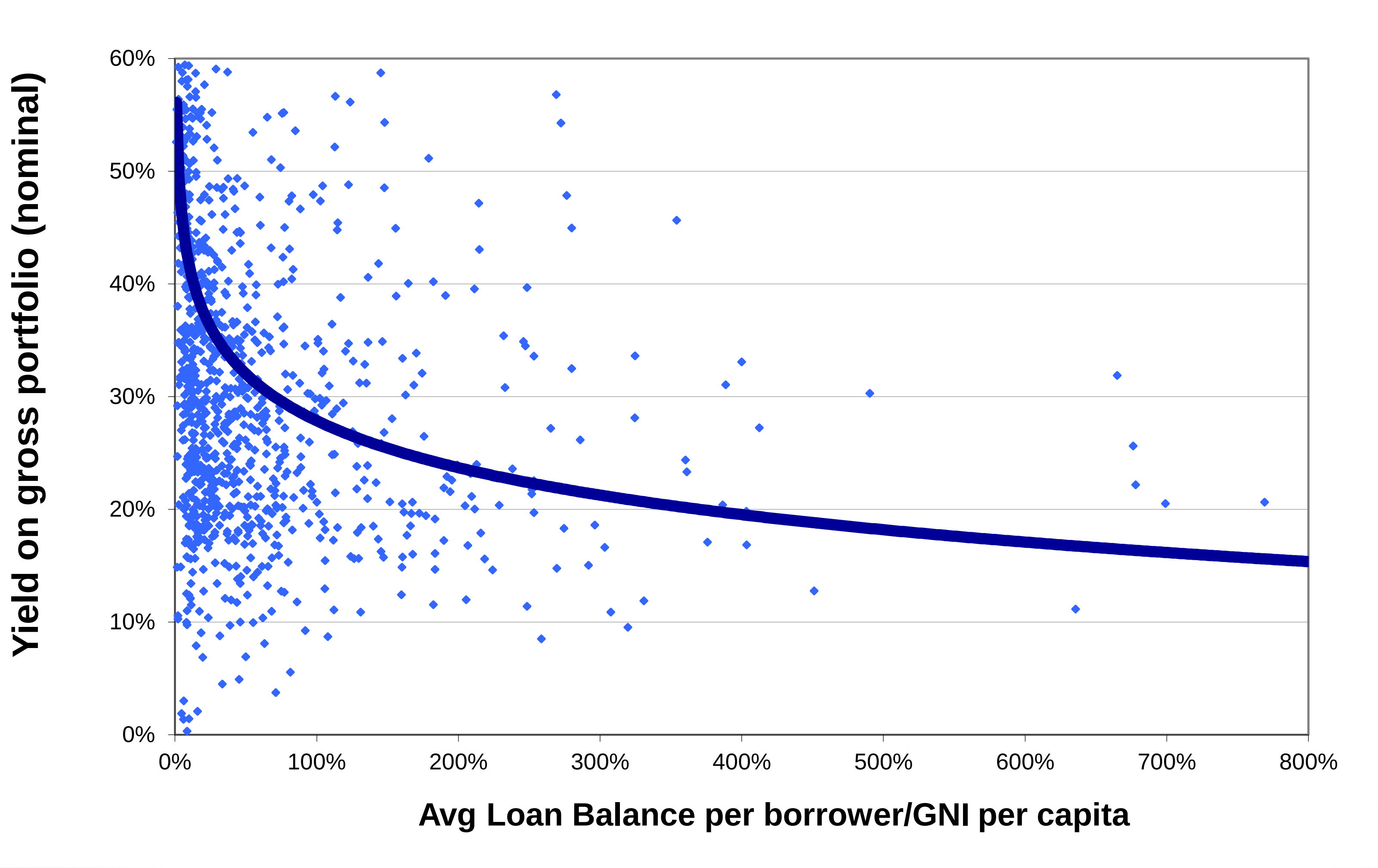
Microfinance Information eXchange

- Largest industry data source on finances of microfinance institutions
  - Biased toward commercially-focused lenders.
- Access to disaggregated data
  - Allows adjustment for implicit subsidy.
- 1336 observations max,
  - Fewer for some variables.
- Cross-section of most-recent observations.

Different Business Models: Smaller Loans Entail Higher Costs

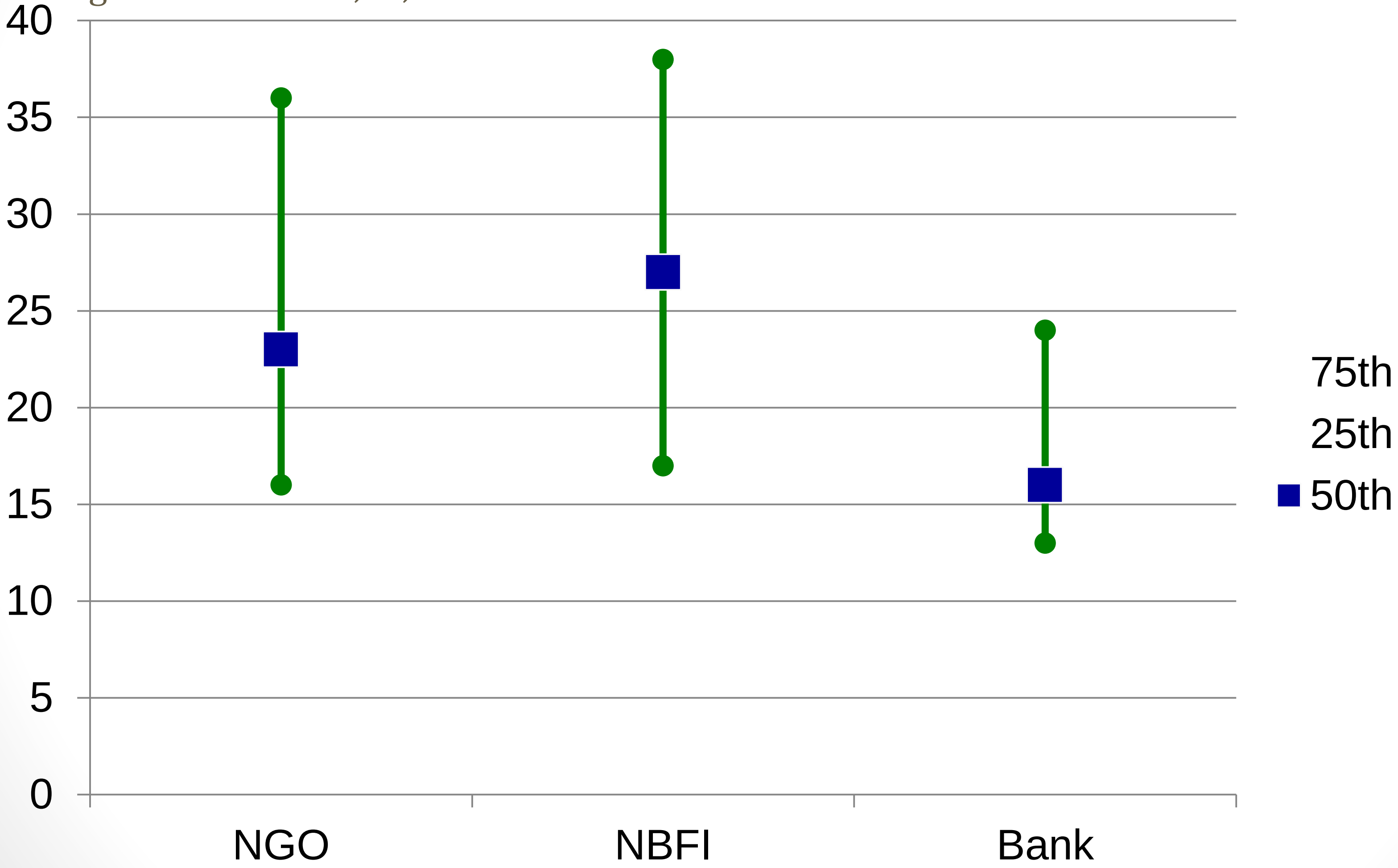


…And thus Higher Interest Rates

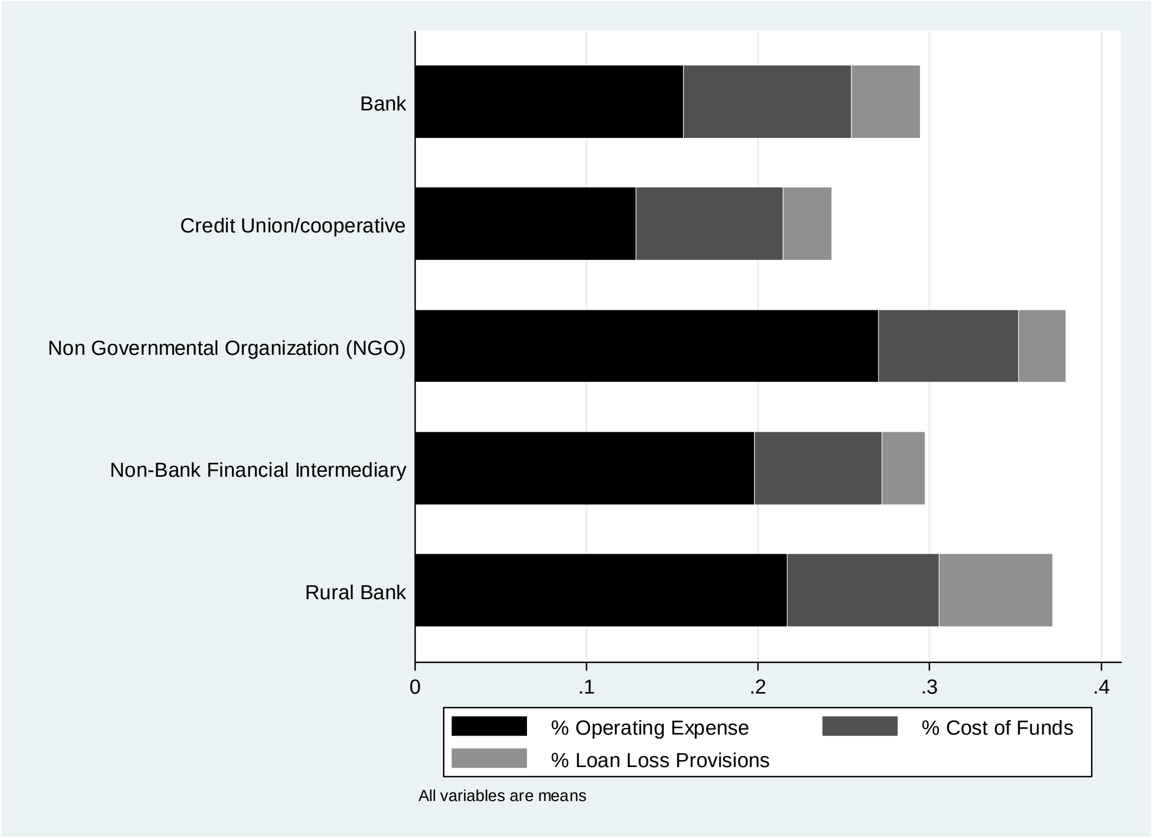


And MFI types cater to different market segments

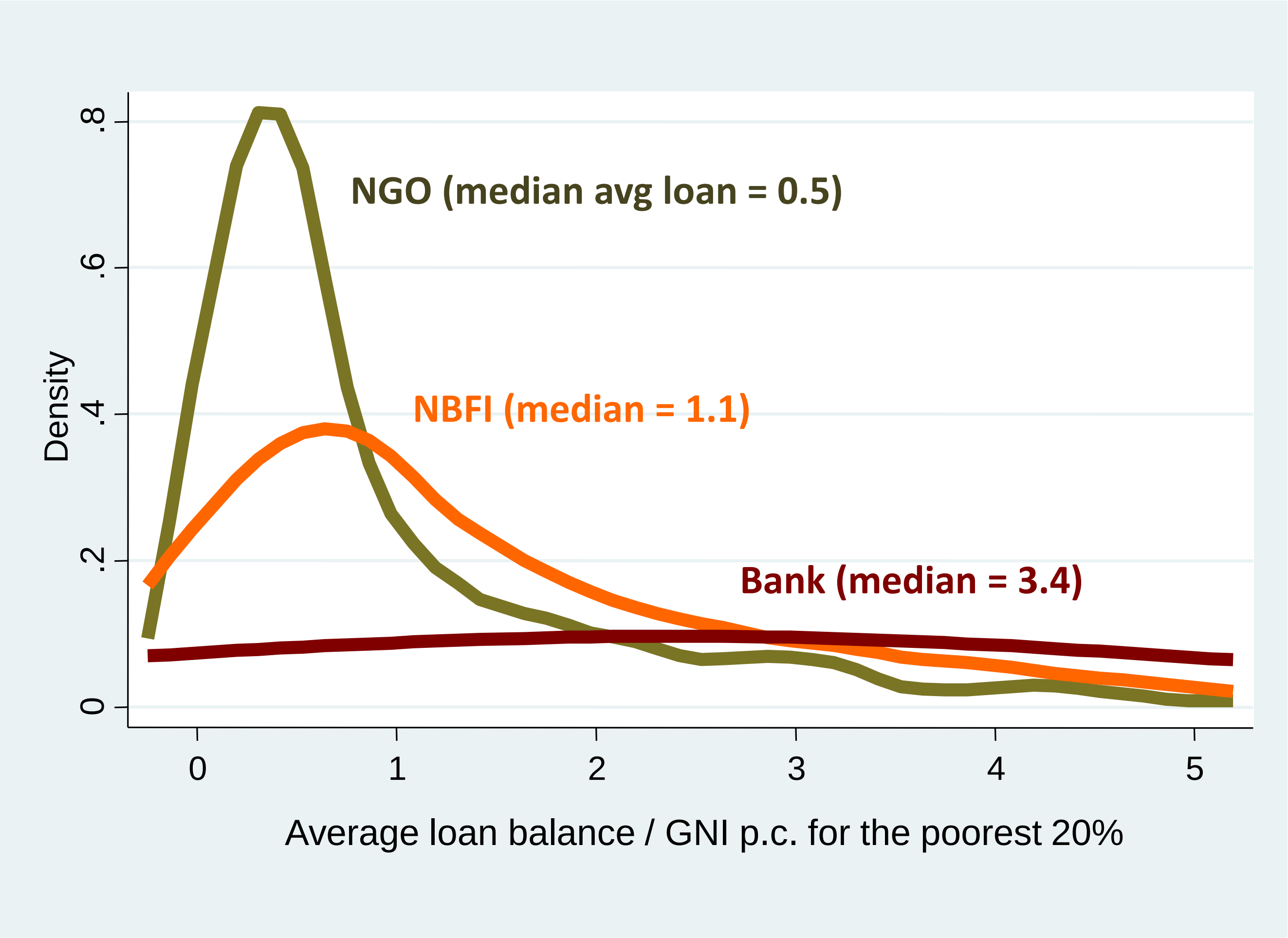
Real portfolio yield
Average interest and fees, %, 2009



Composition of costs
(Divided by Gross Loan Portfolio)

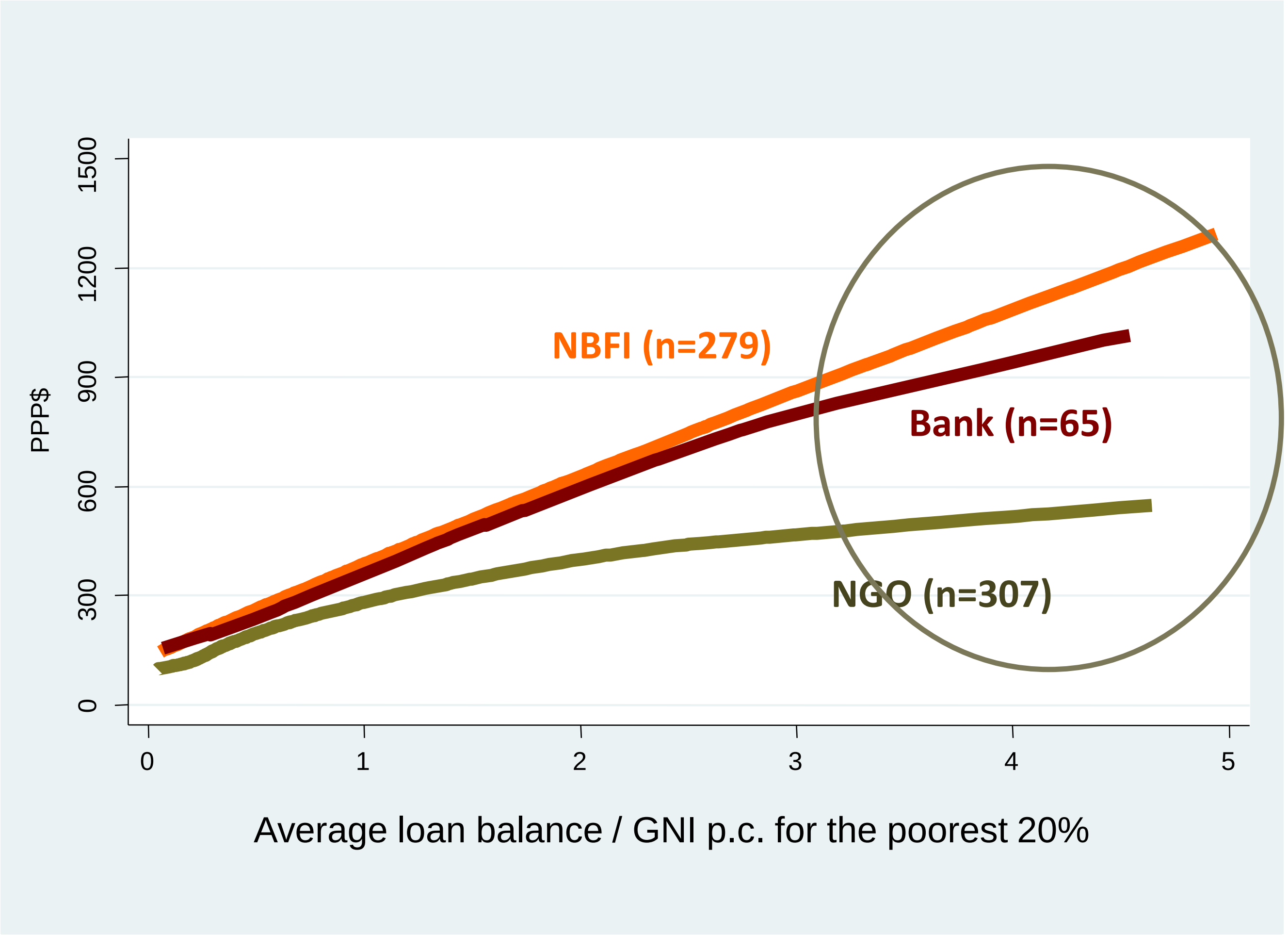


NGOs, Nonbank Financial Institutions, and Banks



A major accomplishment: Innovation to reduce cost per customer

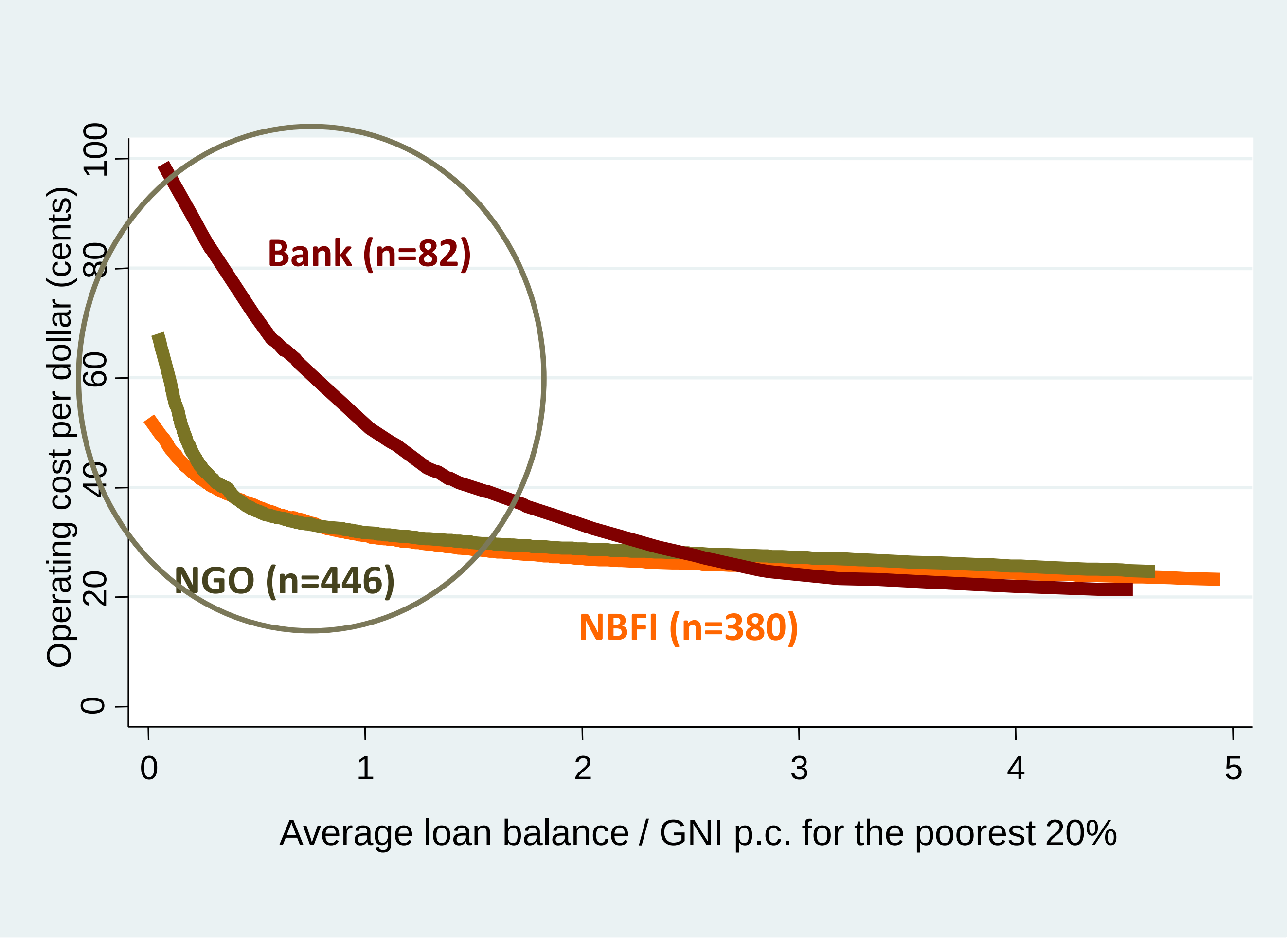
Operating expense per borrower, PPP$



A large and durable tension:

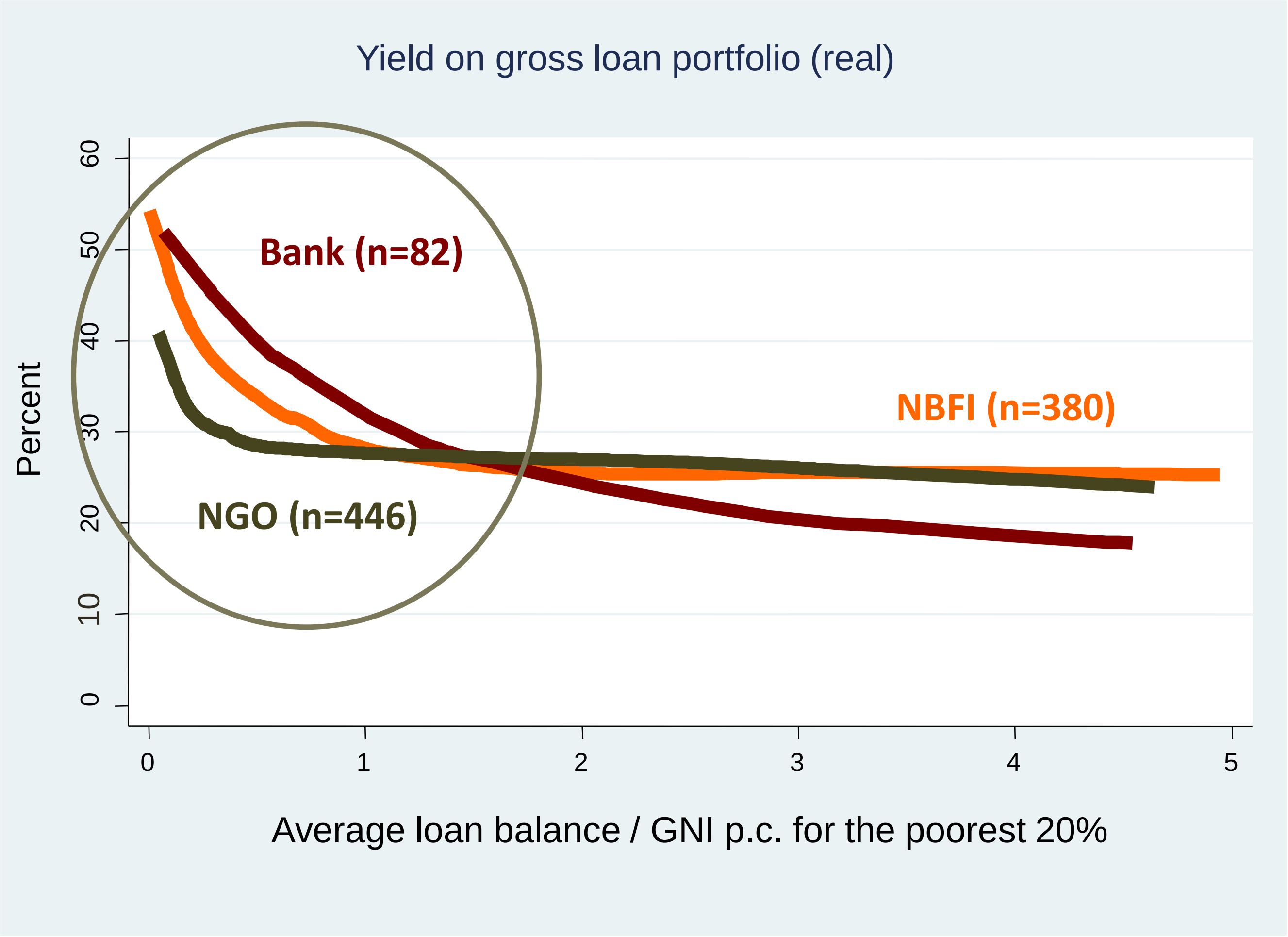
Small transaction sizes mean high cost per unit transacted

Operating expense per dollar lent



Response: raise prices on the low-end

Average real interest rates



Part II: Commercial Microfinace, Greenfields and the "IFC" Model

Based on work with

Greta Bull, IFC

Sven Harten, IFC

Ippei Nishida, World Bank (now at Hitachi Research)

IFC-MasterCard Partnership for Financial Inclusion in Sub-Saharan Africa

- Provide technical assistance to participating African microfinance institutions
- Enable MFIs to grow their numbers of accounts (primarily, loan and savings) and clients.
- Substantial *research, evaluation,* and *knowledge* component designed to distill lessons
- Emerging research agenda (RCTs) on alternative delivery channels
    - Agent banking
    - Mobile Financial Services

The Greenfield Model

- Created without any pre-existing organization
- Standard operating procedures disseminated by a central group (typically a holding company “HC”).
- HC holds majority stake; plays strong role in governance, management, and branding
- Typically majority-owned by foreign entities
- Two types of HCs
  - Consulting firm led (European): Top-down approach
    - Deep commitment to branded retail banking networks spanning multiple countries
    - Investment by DFIs (AfDB, EIB, IFC, KfW)
  - Network Support Organization led: Bottom-up approach
    - Consolidating existing affiliates, adding new greenfields

Source: Earne at al. 2014.

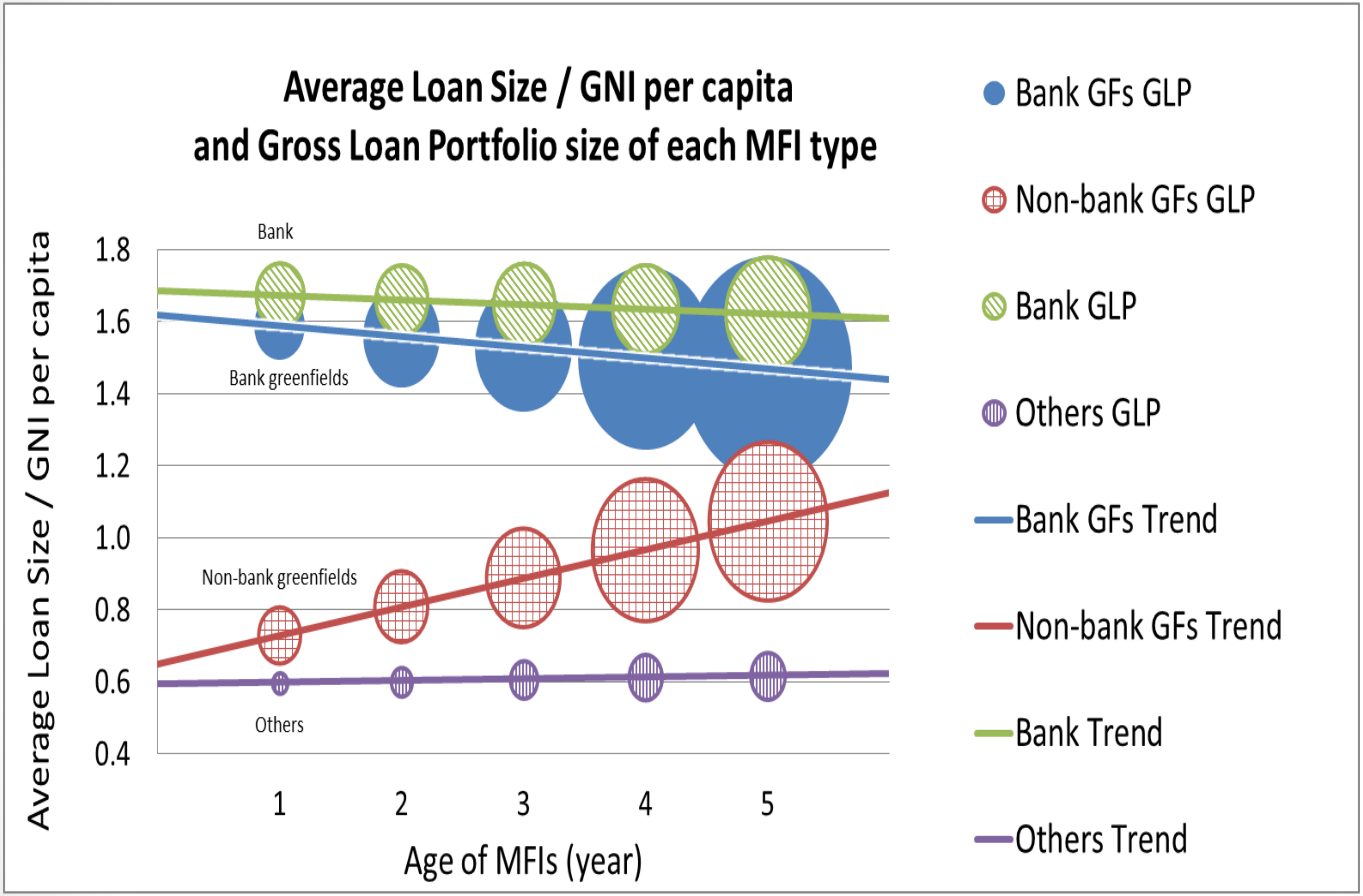
Table 1. MFI name and Country Location: Bank greenfields, Non-bank greenfields & Non-greenfields

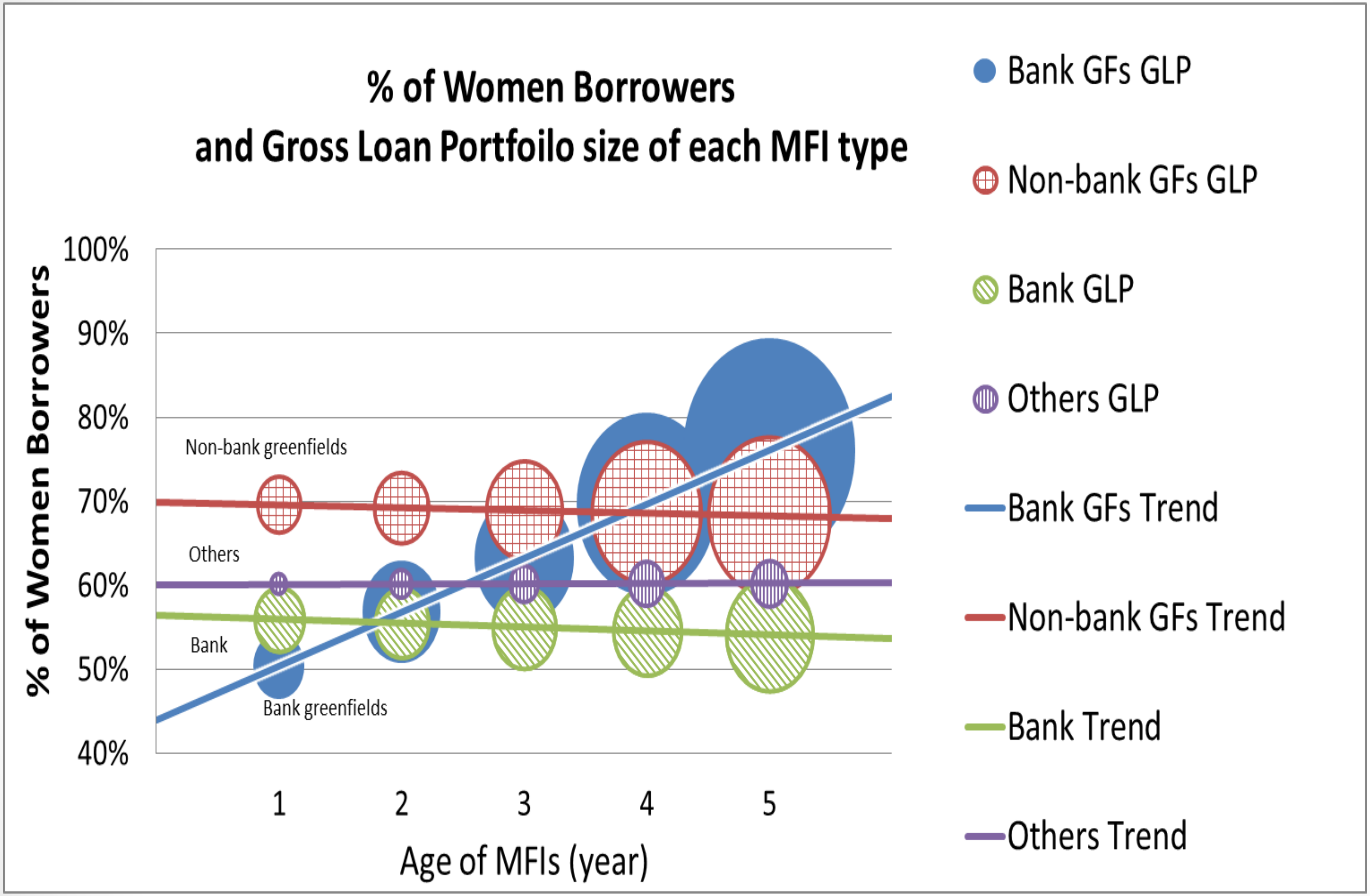
						Is an institution included in the regression model (3) in Table 2-4		
Category	MFI name	Country	Years	Predominant lending style	Average loan size / GNI per capita (median)	Average loan size / GNI per capita	% of female borrowers	OSS
Bank greenfields	Accion Cameroon	Cameroon	2009 - 2012	60%Ind, 40% grp	0.98	X		X
	Advans Cameroon	Cameroon	2007 - 2012	91% Ind, 9% grp	0.90	X	X	X
	Advans DRC	Democratic Republic of the Congo	2008 - 2012	Individual	10.46			
	ProCredit DRC	Democratic Republic of the Congo	2005 - 2012	Individual	20.58			X
	MicroCred Ivory Coast	Cote d'Ivoire (Ivory Coast)	2009 - 2012	Individual	0.70			
	Accion Ghana	Ghana	2008 - 2012	Individual	0.71	X	X	X
	Advans Ghana	Ghana	2008 - 2012	Individual	0.43	X	X	X
	ProCredit Ghana	Ghana	2004 - 2010	Individual	1.54	X	X	X
	Access Liberia	Liberia	2008 - 2012	Individual	2.58	X	X	X
	Access Madagascar	Madagascar	2007 - 2012	Individual	2.19	X	X	X
	MicroCred Madagascar	Madagascar	2006 - 2012	Individual	2.12	X	X	X
	ProCredit Mozambique	Mozambique	2007 - 2008	Individual	2.48			
	Access Nigeria	Nigeria	2008 - 2012	Individual	1.01	X	X	X
	Accion Nigeria	Nigeria	2006 - 2011	Individual	0.62	X	X	X
	MicroCred Nigeria	Nigeria	2010 - 2012	Individual	0.44	X		X
	Fides Senegal	Senegal	2011 - 2012	10% Ind, 90%g rp	0.15	X		X
	MicroCred Senegal	Senegal	2007 - 2012	Individual	1.21	X	X	X
	ProCredit Sierra Leone	Sierra Leone	2007 - 2010	N/A	3.77			X
	Access Tanzania	Tanzania	2007 - 2012	Individual	3.51	X	X	X
	Advans Tanzania	Tanzania	2011 - 2012	Individual	2.46			
	Access Zambia	Zambia	2011 - 2012	Individual	0.85			X
Non-bank greenfields	PAMF-BFA	Burkina Faso	2006 - 2008	91%grp, 9% Ind	N/A			X
	ACEP Cameroon	Cameroon	2001 - 2010	Individual	1.88	X	X	X
	FINCA DRC	Democratic Republic of the Congo	2003 - 2012	50%grp, 50% Ind	1.06			
	Opportunity DRC	Democratic Republic of the Congo	2005 - 2012	N/A	1.77			
	ASA Ghana	Ghana	2007 - 2012	Group	0.12			
	OISL	Ghana	2004 - 2010	72%grp, 28% Ind	0.35	X	X	X
	Opportunity Ghana	Ghana	2005 - 2012	N/A	0.32			
	BRAC Liberia	Liberia	2008 - 2012	64%grp, 36% Ind	0.41			
	OIBM	Malawi	2003 - 2010	89% Ind, 11%grp	2.36	X	X	X
	BOM	Mozambique	2005 - 2010	Individual	0.79	X	X	X
	ASA Lagos	Nigeria	2010 - 2012	Group	0.10			
	ASA Nigeria	Nigeria	2009 - 2012	Group	0.09			
	ACEP Senegal	Senegal	1997 - 2010	Individual	2.40	X	X	X
	BRAC Sierra Leone	Sierra Leone	2009 - 2012	Group	0.20			
	BRAC - SS	Sudan	2007 - 2010	Group	0.08	X	X	X
	BRAC Tanzania	Tanzania	2006 - 2012	86%grp, 14% Ind	0.26	X	X	X
	BRAC Uganda	Uganda	2004 - 2012	82% grp; 18% Ind	0.30	X	X	X
Non-greenfields	Finadev Benin	Benin	2006 - 2007	N/A	N/A			
	Faulu - KEN	Kenya	1999 - 2011	83%grp, 17% Ind	0.46	X	X	X
	K-Rep	Kenya	2000 - 2011	Group	1.01	X	X	X
	Opportunity Bank Rwanda	Rwanda	2011 - 2011	62%grp, 38% Ind	0.55	X		

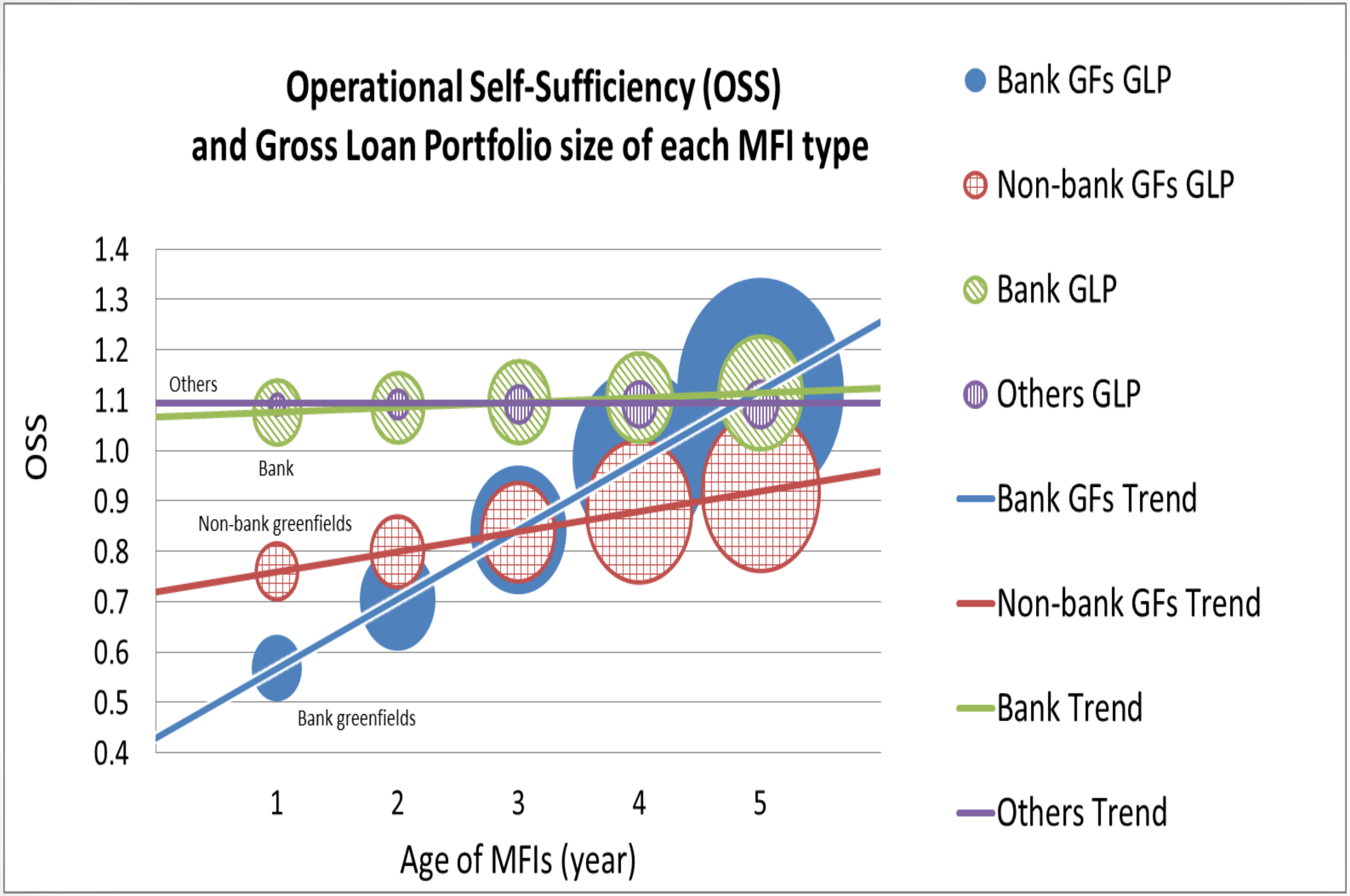
Growth of Greenfields

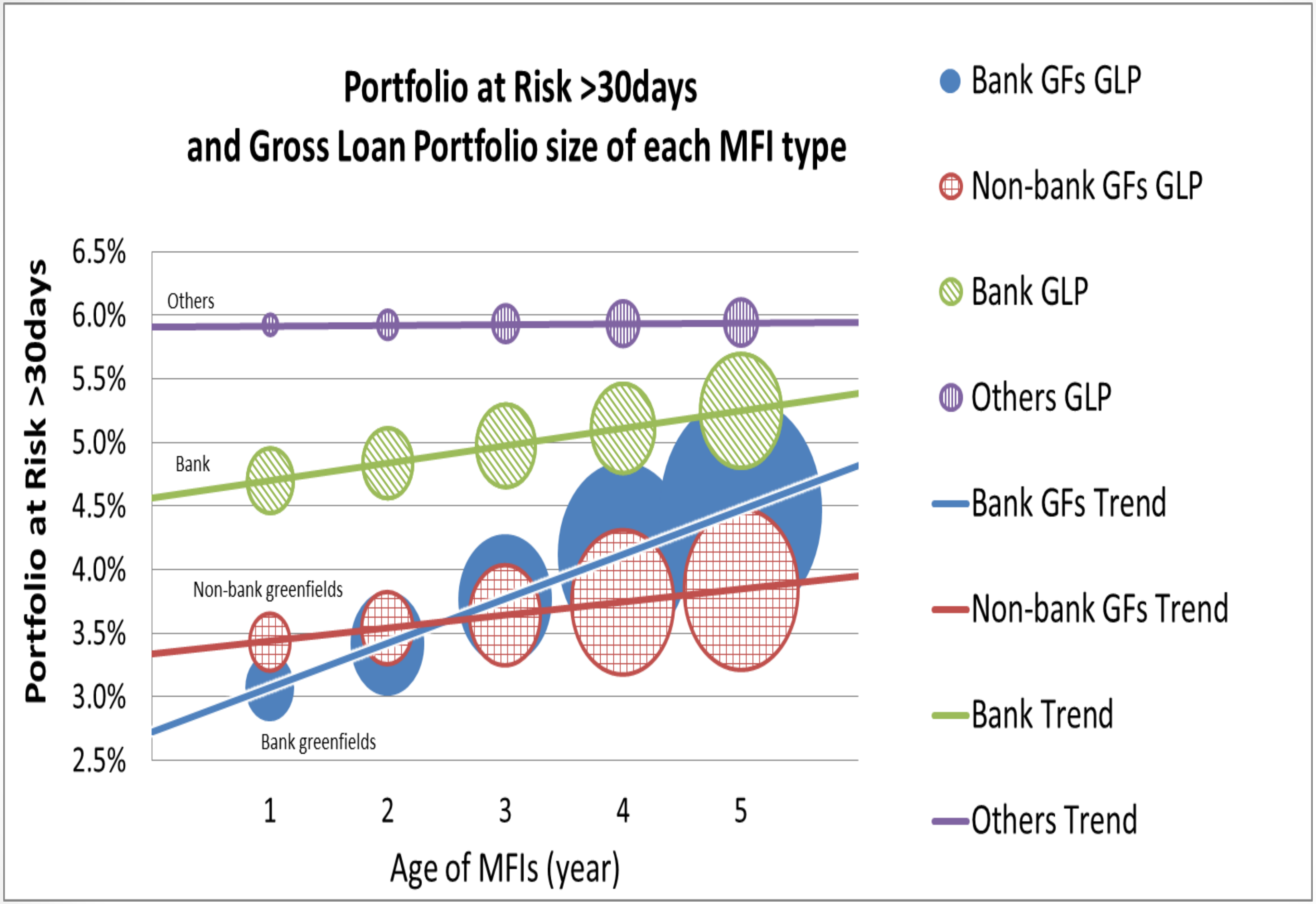
Source: Earne et al., 2014.

	Greenfields			MIX Young Africa
	Month 12	Month 36	Month 60	
No. Staff	131	318	524	69
No. Branches	9	22	31	10
No. Loans Outstanding	9,495	25,009	36,714	11,255
Gross Portfolio ($ million)	2.3	9.2	20.0	2.7
No. Deposit Accounts	7,123	37,460	81,682	18,127
Deposits ($ million)	0.8	8.7	23.1	2.0
PaR 30	3.9%	4.0%	3.4%	9.5%
Operating Exp/Portfolio	200%	53%	36%	113%
Equity ($ million)	3.6	4.3	6.6	1.2
Net income/Assets	-12.4%	-0.1%	3.1%	-2.4%
Net Income/Equity	-44.6%	-0.3%	18.9%	-3.4%


Average Loan Size / GNI per capita
and Gross Loan Portfolio size of each MFI type
Bank
Bank greenfields
Non-bank greenfields
Others
Average Loan Size / GNI per capita
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
1
2
3
4
5
Age of MFIs (year)
Bank GFs GLP
Non-bank GFs GLP
Bank GLP
Others GLP
Bank GFs Trend
Non-bank GFs Trend
Bank Trend
Others Trend


% of Women Borrowers
and Gross Loan Portfoilo size of each MFI type
Bank GFs GLP
Non-bank GFs GLP
Bank GLP
Others GLP
Bank GFs Trend
Non-bank GFs Trend
Bank Trend
Others Trend
100%
90%
80%
70%
60%
50%
40%
% of Women Borrowers
Non-bank greenfields
Others
Bank
Bank greenfields
1
2
3
4
5
Age of MFIs (year)


Operational Self-Sufficiency (OSS)
and Gross Loan Portfolio size of each MFI type
OSS
1.4
1.3
1.2
1.1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
Others
Bank
Non-bank greenfields
Bank greenfields
1
2
3
4
5
Age of MFIs (year)
Bank GFs GLP
Non-bank GFs GLP
Bank GLP
Others GLP
Bank GFs Trend
Non-bank GFs Trend
Bank Trend
Others Trend


Portfolio at Risk >30days
and Gross Loan Portfolio size of each MFI type
Portfolio at Risk >30days
6.5%
6.0%
5.5%
5.0%
4.5%
4.0%
3.5%
3.0%
2.5%
Others
Bank
Non-bank greenfields
Bank greenfields
1
2
3
4
5
Age of MFIs (year)
Bank GFs GLP
Non-bank GFs GLP
Bank GLP
Others GLP
Bank GFs Trend
Non-bank GFs Trend
Bank Trend
Others Trend

Part III: Alternative Models, Role of Subsidy

Again, based on work with

Asli Demirgüç-Kunt, World Bank
Jonathan Morduch, New York University

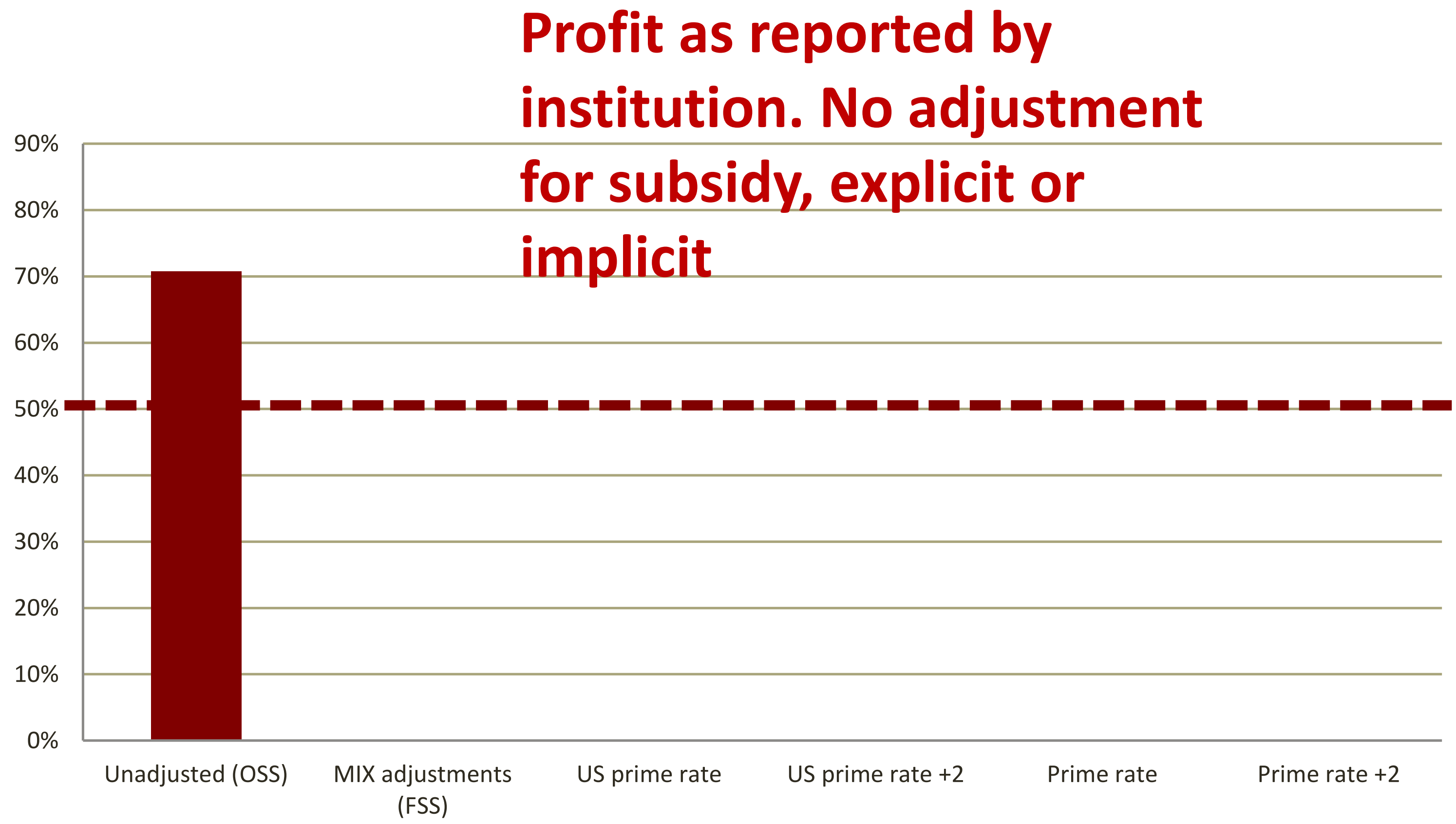
Back to the Promise of MF

"No one argues seriously that finance-based programs will be the answer for truly destitute households, but the promise remains that microfinance may be an important aid for households that are not destitute but still remain considerably below poverty lines…..

The tension is that the scale of lending to this group is not likely to permit the scale economies available to programs focused on households just above poverty lines. Subsidizing may yield greater social benefits than costs here."

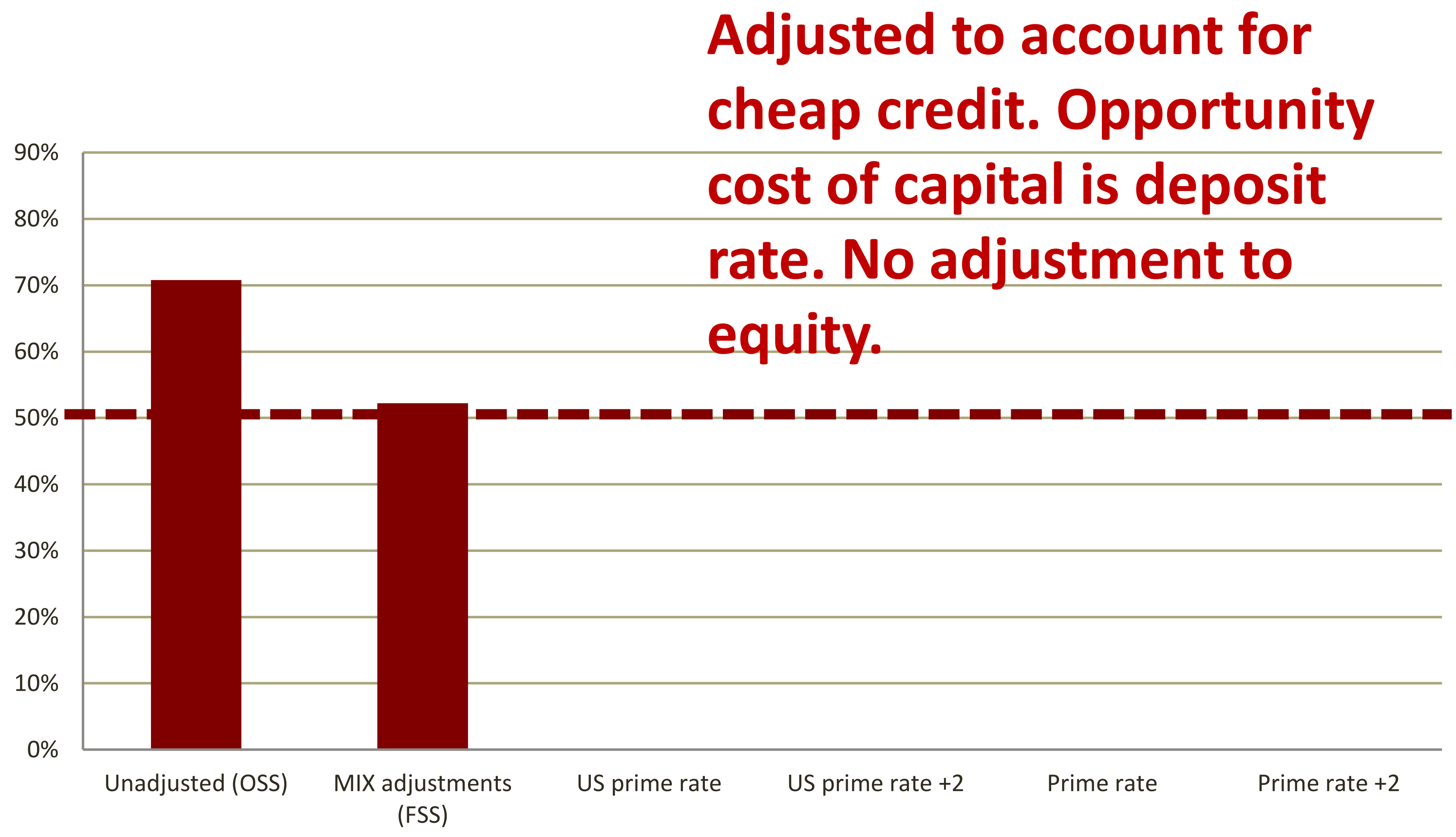
What institutions report

% of institutions that are profitable



What donors report

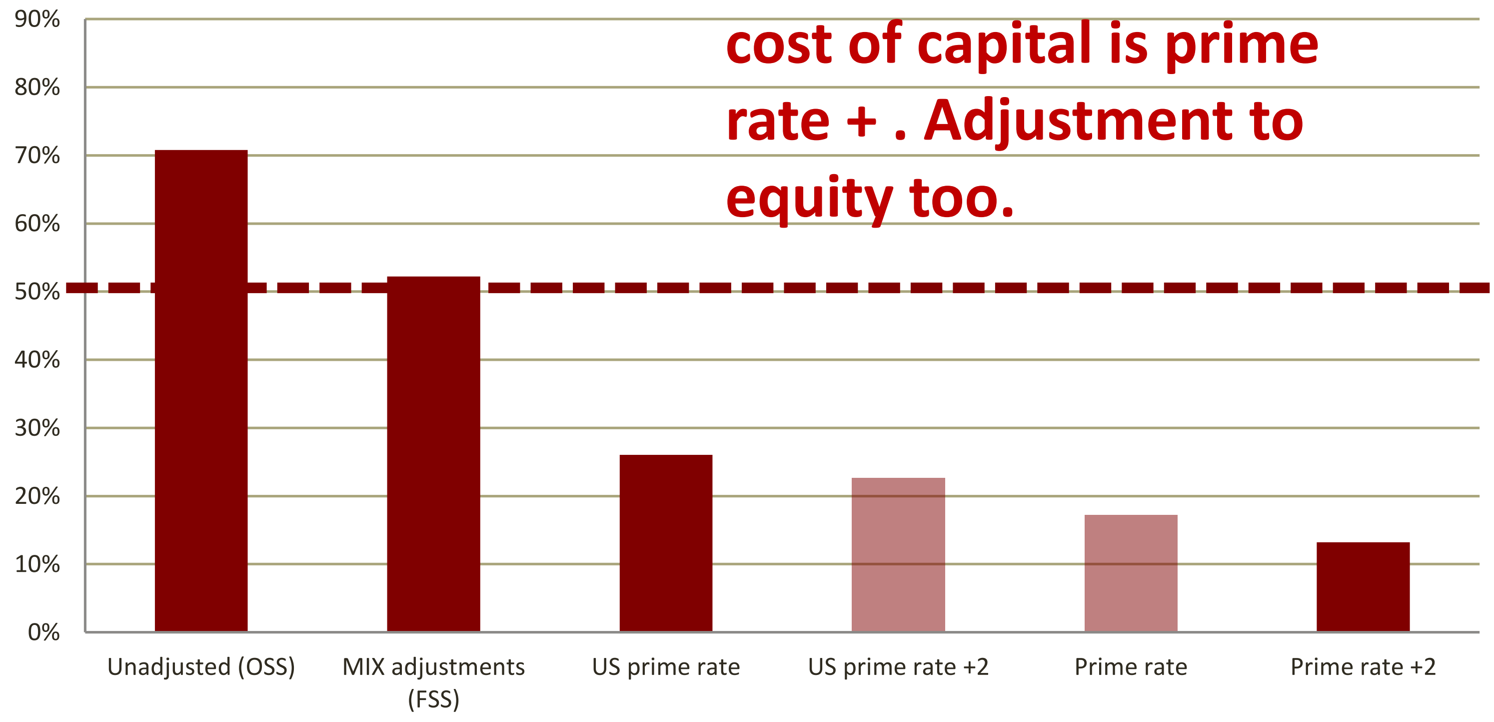
% of institutions that are profitable



What economics/finance suggests

% of institutions that are profitable

Adjusted to account for cheap credit. Opportunity cost of capital is prime rate + . Adjustment to equity too.



Adjustments

Subsidy =

Opportunity costs for equity capital

+ Profit before tax

+ Adjusted in kind subsidy

+ Opportunity costs for loan capital (opp. cost of capital - actual paid rate)

Preferred opp cost of capital = local prime rate + 2%

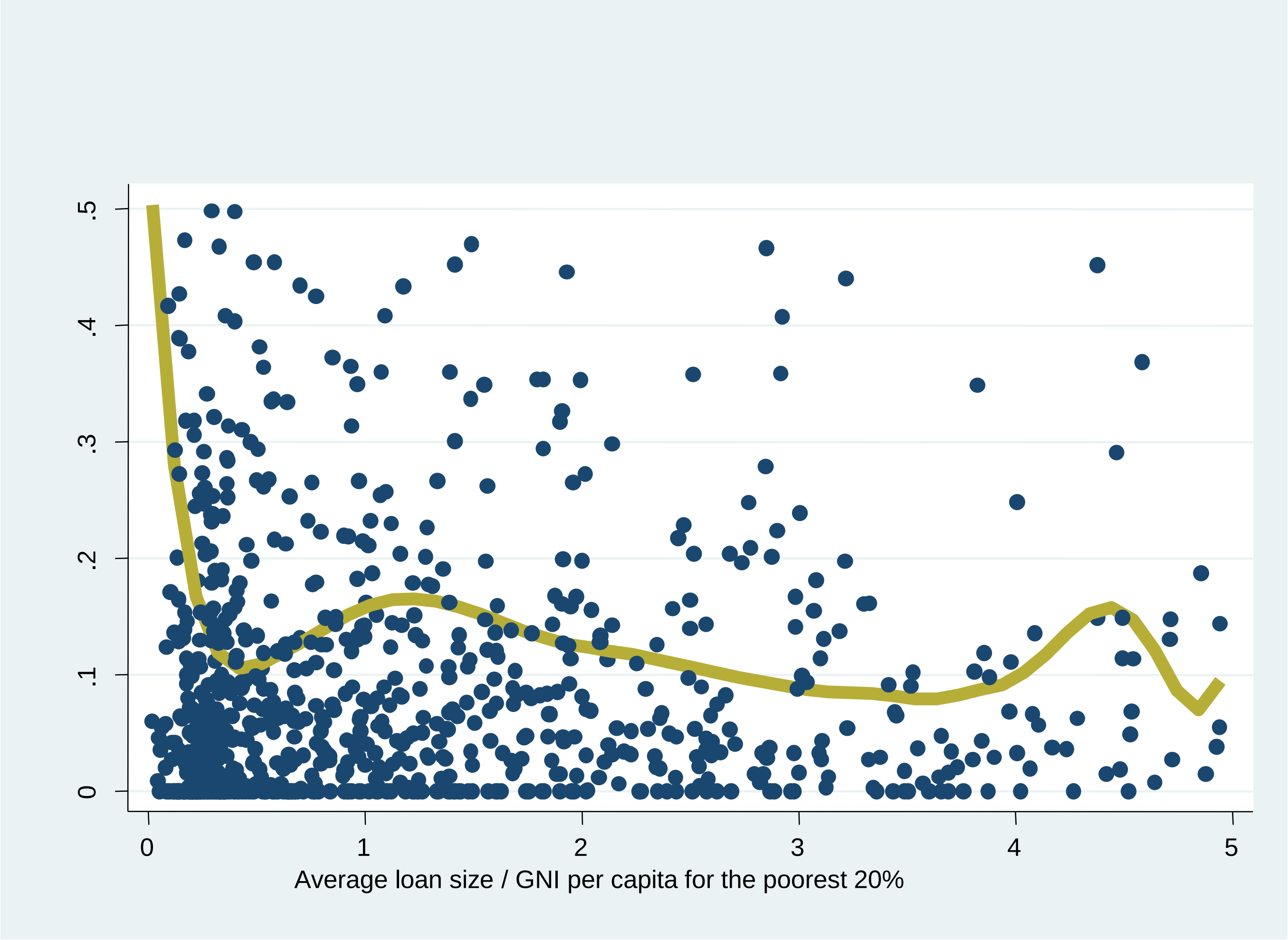
What’s the question?

By adjusting for realistic opportunity cost of capital:

Q: Would institution earn profit if they *operated the same way* but had to pay the market rate of capital?

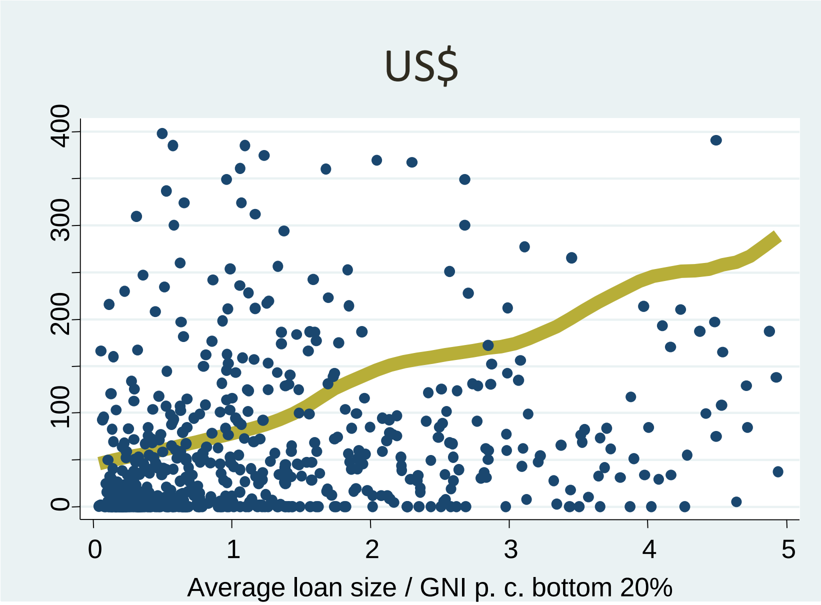
Relatively flat: Subsidy per dollar lent

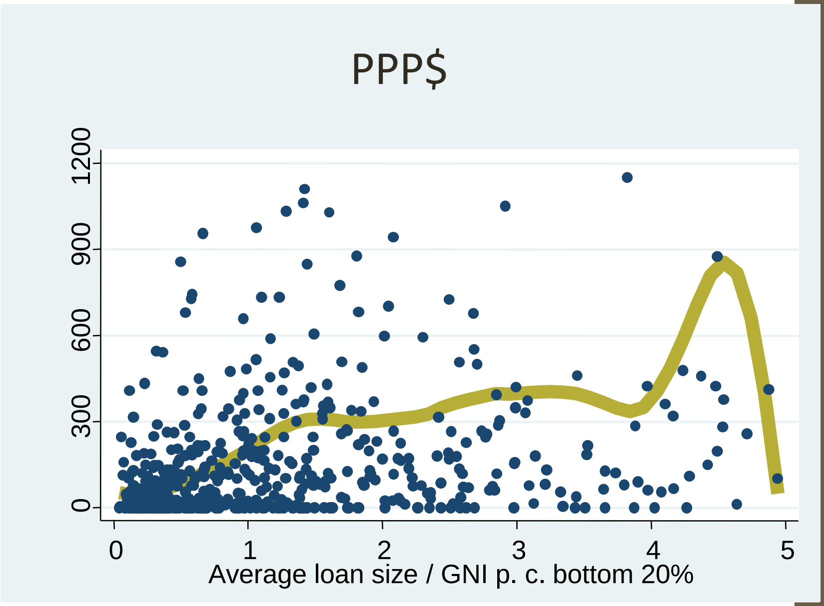
γ=local prime + 2% (obs = 973)



Upward sloping: Subsidy per borrower

γ=local prime + 2% (obs = 737, 690)





Subsidy per borrower

Most recent observations 2005-2009

	Mean	25th percentile	Median	75th percentile	Obs
Full sample	145	4	40	122	762
Bank	241	25	103	259	65
NGO	117	6	34	85	285
NBFI	178	4	37	144	250
For-profit	168	0	21	129	291
Not-For-profit	131	9	46	116	470

Some of the subsidies are large

PPP adjusted subsidy per borrower

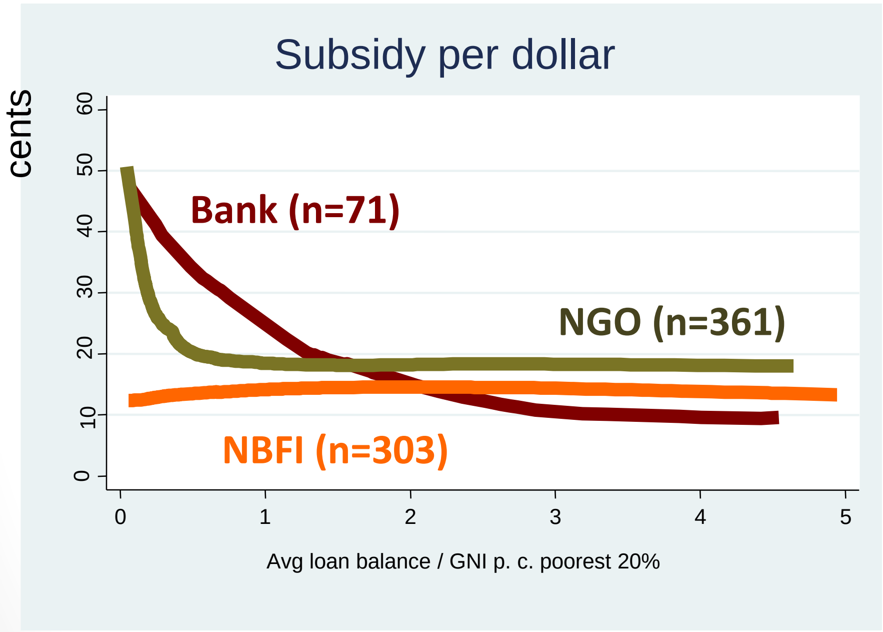
Most recent observations 2005-2009

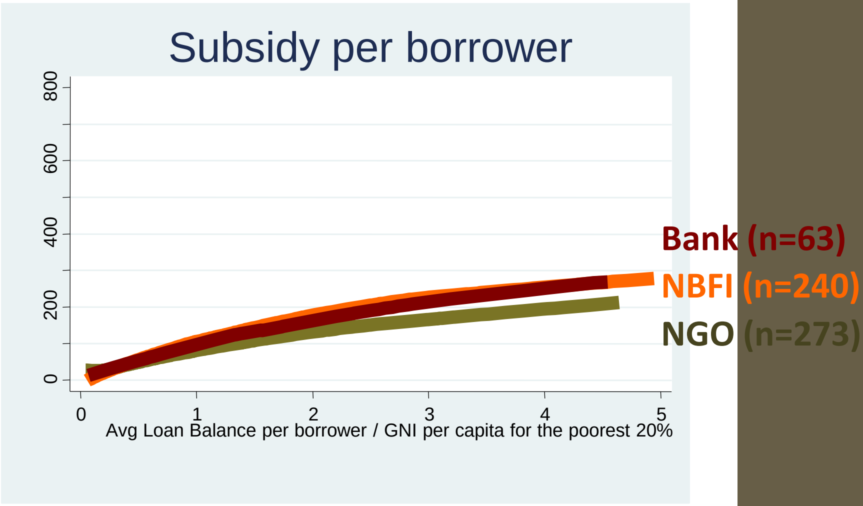
	Mean	25th percentile	Median	75th percentile	Obs
Full sample	267	6	70	246	694
Bank	508	42	210	566	60
NGO	206	11	60	176	260
NBFI	302	10	70	268	241
For-profit	288	0	34	258	285
Not-For-profit	131	9	46	117	470

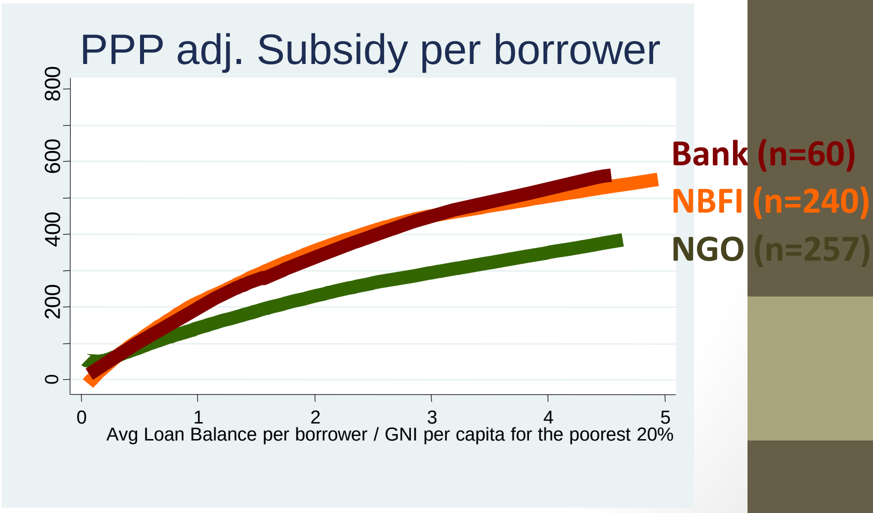
Large… especially in PPP terms

Subsidy: by institution

γ=local prime + 2%

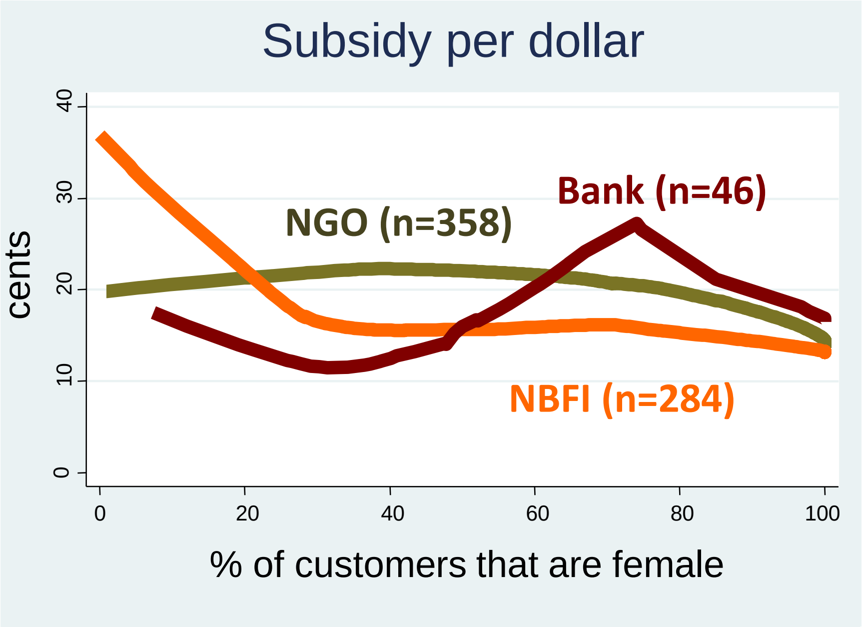


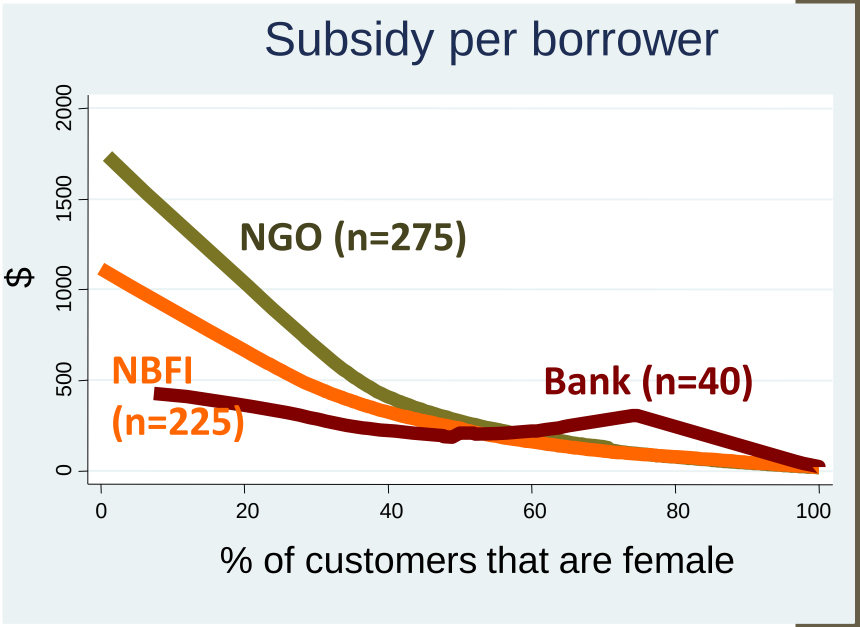




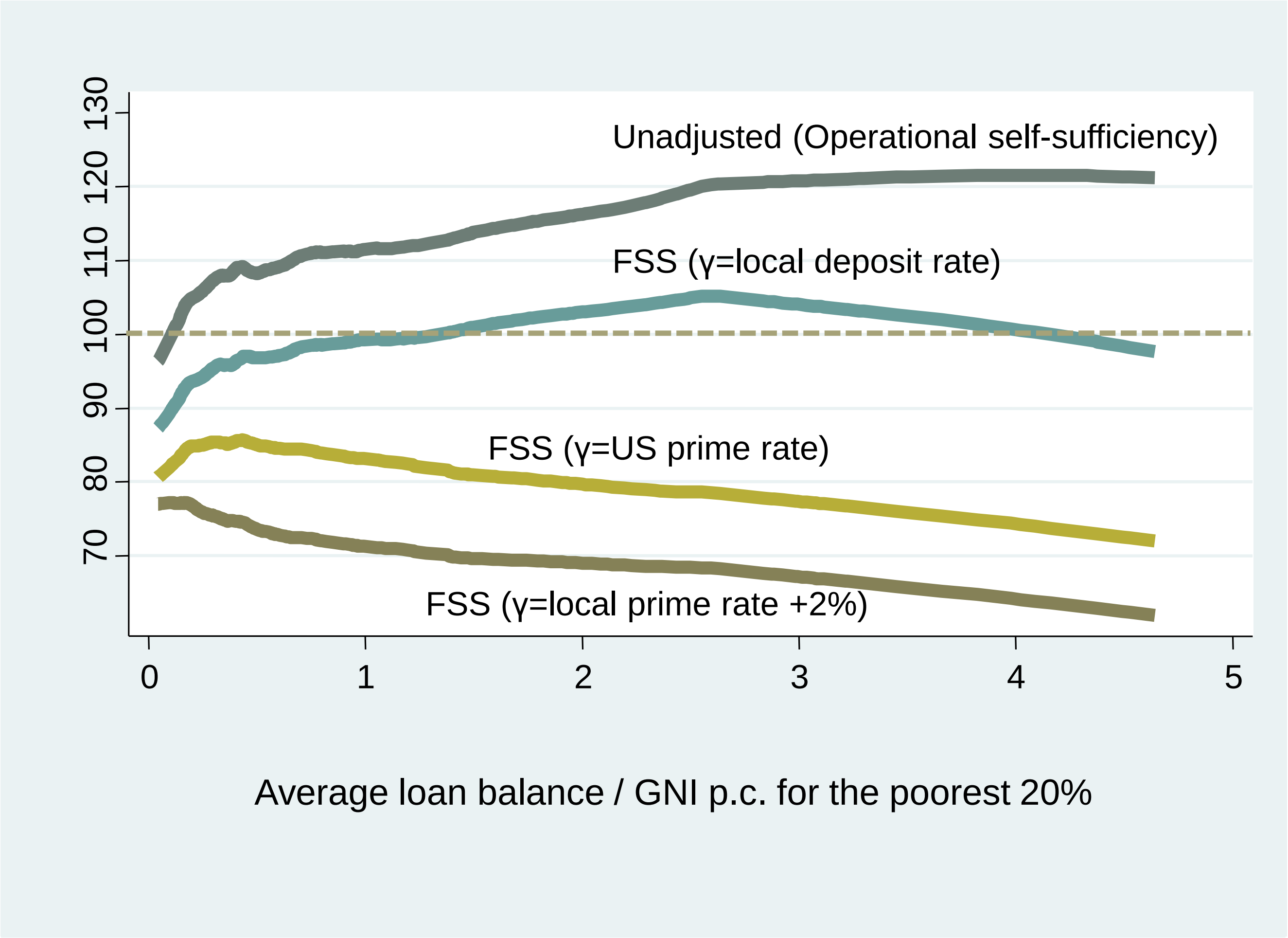
Subsidy : by institution

By gender of customers

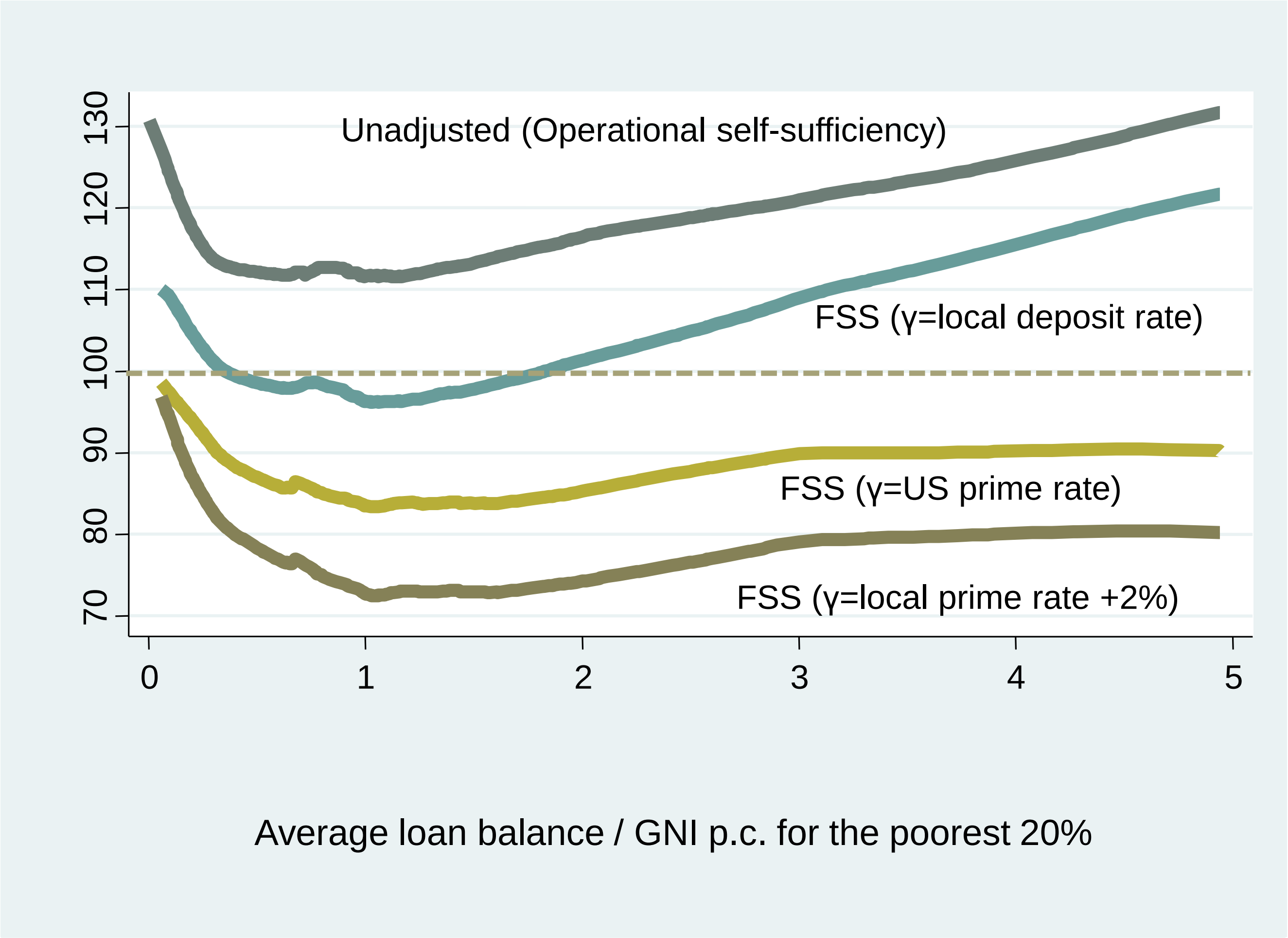




NGOs: Financial self-sufficiency



NBFIs: Financial self-sufficiency



Persistence of Subsidies

Sample	Mean	25th pctile	Median	75th pctile	Obs
If age < 10 years					
Age	5.20	3.00	5.00	7.00	562
Average loan size per GNI at bottom 20th percentile	2.23	0.29	0.78	2.02	529
Subsidy per dollar lent (percent)	21	2	10	24	409
Subsidy per borrower ($)	191	5	46	167	404
If age >=10					
Age	18.44	12.00	15.00	21.00	761
Average loan size per GNI at bottom 20th percentile	2.53	0.47	1.16	2.68	750
Subsidy per dollar lent (percent)	10	1	5	13	615
Subsidy per borrower ($)	126	2	32	94	599

Conclusions ~2009-2010

"The clash between profit-driven Banco Compartamos and the 'social business' model of Grameen Bank offers a false choice. Commercial investment is necessary to fund the continued expansion of microfinance, but institutions with strong social missions, many taking advantage of subsidies, remain best placed to reach and serve the poorest customers, and some are doing so at a massive scale. The market is a powerful force, but it cannot fill all gaps."

CDKM, Journal of Economic Perspectives, 2009.

Updating 2010 conclusions

- General gist still probably correct
- Cost component still crucial for designing business models to reach the poorest.

BUT:

- Commercial microfinance a good vehicle to achieve scale among the (somewhat less) poor
- Reaching the poorest with less reliance on subsidy remains a challenge
    - Technological innovation, mobile financial services
    - Nearer points of contact, agent banking
    - Understanding client needs better
        - Commitment savings devices
        - Conditional cash transfer: accounts, electronic payments
        - More flexible loan repayment schedules

Part IV: Alternative Delivery Channels, Reducing Costs

Based on work with

Joshua Blumenstock, Univ. Washington

Miriam Bruhn, World Bank

Sinja Buri, IFC

Xavier Gine, World Bank

Sven Harten, IFC

Anca Bogdana Rusu, World Bank

Quick Detour: Interpreting Modest Benefits

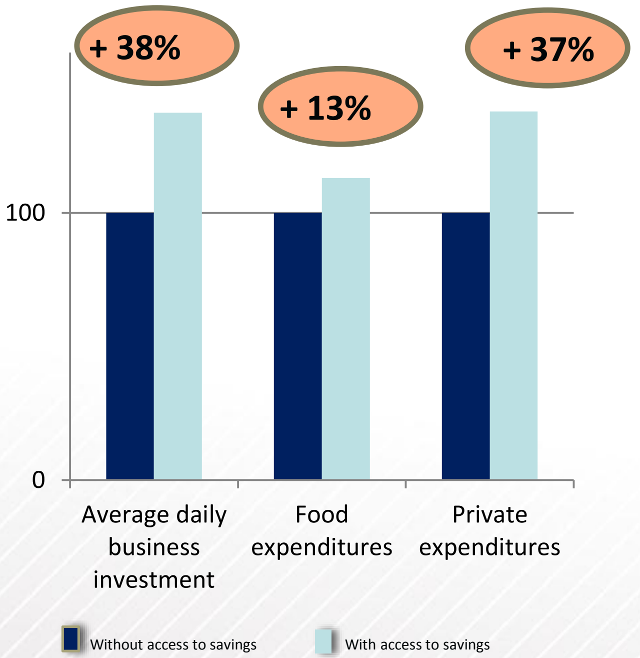
Banerjee, Karlan, Zinman, AEJ: Applied, Jan. 2015

- Statistical power remains a challenge
- Insufficiently long time horizons (?)
- External validity: Extending to other contexts
- Heterogeneous effects
- Spillover effects/General Equilibrium
- Effects on inframarginal borrowers
- Need to vary terms of the loan contract
- Microfinance is more than microcredit

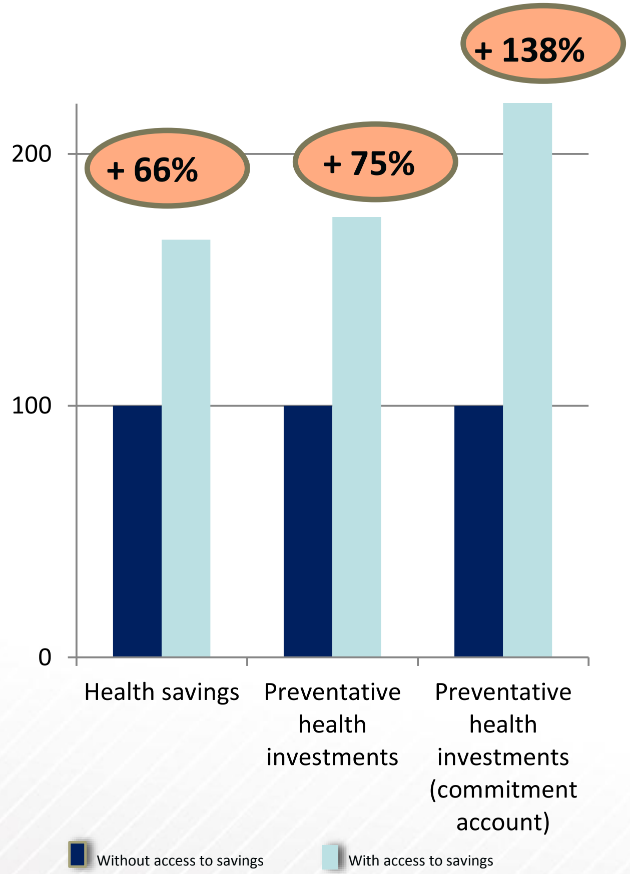
Microeconomic Level: Savings (From Cull, Ehrbeck, Holle, CGAP Focus Note 92, April 2014.)

Savings help manage cash flow spikes, smooth consumption and build working capital

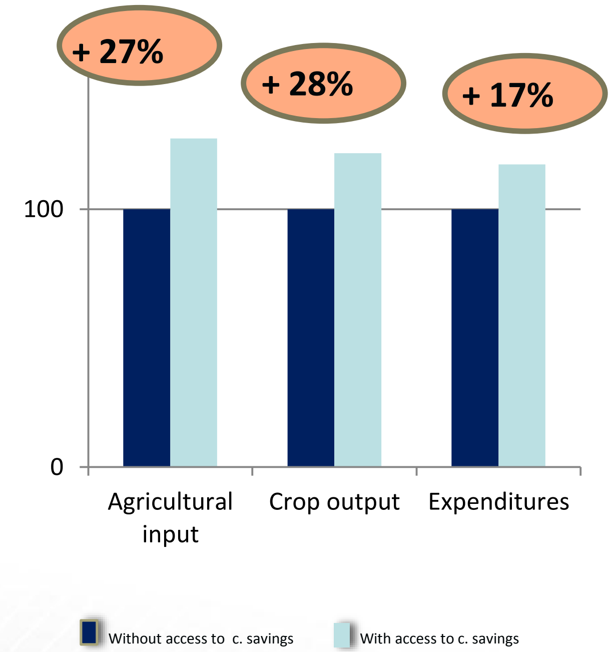
- **Business investments of women (Kenya)***



Health savings and investments (Kenya)**



Agricultural activity (Malawi)***



CGAP

* Dupas, Pascaline et al. (2012a). Savings constraints and microenterprise development: evidence from a field experiment in Kenya. AEJ: Applied Economics. Forthcoming.
** Dupas, Pascaline et al. (2012b). Why don't the poor save more? Evidence from health savings experiments, NBER Working Paper.
*** Brune, Lasse et al. (2013): Commitments to save. A field experiment in rural Malawi. Working Paper.

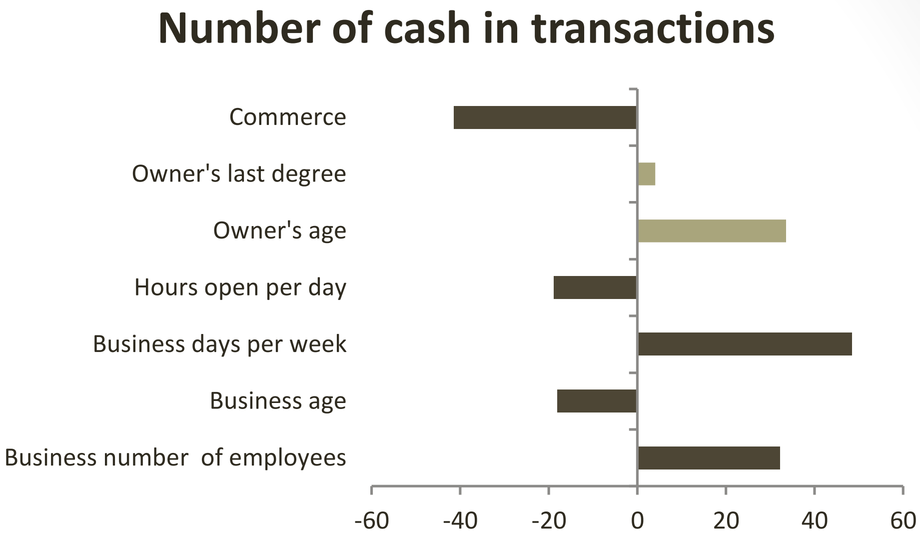
A More Modest Assessment of Modest Benefits

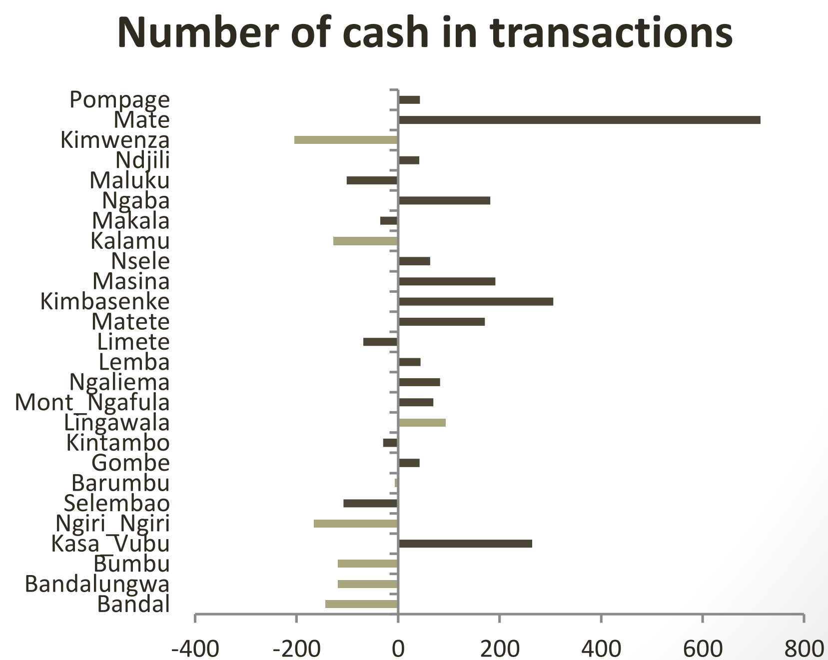
"We must think beyond the standard microcredit model. Modern microfinance – savings and insurance, and more flexible credit products – often has generated larger impacts than simple credit….Financial services can make important differences in people's lives, but we need more innovation and evidence to determine what is best to do, and meanwhile we should set our expectations appropriately."

Dean Karlan, Innovations for Poverty Action (IPA) Press Release, 1/22/2015

Alternative Delivery Channels (1): Agent Banking in DRC

VARIABLES	Number of cash in transactions	Valume of cash in transactions
business_age	-0.702	-0.00300
	(2.482)	(0.0168)
business_number_employees	3.365	0.0177
	(4.219)	(0.0285)
Commerce	-134.4***	-0.514**
	(35.67)	(0.241)
business_daysperweek	23.25	-0.212
	(41.15)	(0.278)
hrsopenperday	-4.960	-0.0605
	(7.165)	(0.0484)
owner_age	0.661	0.0229*
	(1.726)	(0.0117)
last_degree	82.77**	0.281
	(34.67)	(0.234)
Funa	69.14	0.296
	(48.92)	(0.330)
Mont_Amba	147.1***	1.303***
	(53.25)	(0.360)
Tshangu	174.5***	0.572*
	(49.00)	(0.331)
Other_KinEst	317.5***	1.248**
	(79.65)	(0.538)
liquiditytotal	23.42***	0.0502
	(5.529)	(0.0373)
clientservicetotal	15.88	0.0777
	(23.74)	(0.160)
performancetotal	6.756	0.165*
	(14.11)	(0.0953)
brandingtotal	31.88***	0.554***
	(9.597)	(0.0648)
Constant	-363.3	5.791***
	(273.6)	(1.848)
Observations	259	259
R-squared	0.301	0.362
Standard errors in parentheses		
*** p<0.01, ** p<0.05, * p<0.1		





Alternative Delivery Channels (1): Agent Banking in DRC

- Agent Network Density Experiment
  - Work with Finca DRC to randomly assign high/low density in their roll-out of 200-300 new agents
  - 60-80 areas assigned high, 60-80 assigned low
  - Examine what the density of the agent network implies for users of Finca services, and for Finca agents
  - Also examine how results differ depending on agent proximity to a branch, liquidity management methods

Alternative Delivery Channels (2): Agent Banking in Senegal

- Topic: Saving with Branches versus Agents, MicroCred Senegal, Encouragement RCT

HH Survey – Breakdown of sample over survey groups

2500 respondents for the HH survey were selected based on characteristics that were collected during a filter survey with 8000 respondents.

2500 people selected are among those that are the ones that are most likely to open a savings account in the future (based on own predictions).

The HH survey will be repeated with the same respondents one year after the initial survey.

Branches v. Agents, Savings Encouragement RCT, Senegal

1) <u>*Control group*</u>

500 people completed the questionnaire but will not receive any incentive or information about MicroCred savings account

2) <u>*Treatment group*</u>

2000 people in total which were randomly assigned into 4 different treatment groups

(a) **Treatment subgroup 1**

500 people will receive savings *account information* and will be sent to open an account at a *branch*

(b) **Treatment subgroup 2**

500 people will receive savings *account information* and will be sent to open an account at an *agent*

(c) **Treatment subgroup 3**

500 people will receive *account information, initial amount of 1500 CFA* transferred to their account (if they open one)

and will be sent to open an account at a *branch*

(d) **Treatment subgroup 4**

500 people will receive *account information, initial amount of 1500 CFA* transferred to their account (if they open one)

and will be sent to open an account at an *agent*

Alternative Delivery Channels (3): Mobile Fin Services, Ghana

Blumenstock, Harten, Khan, Ngahu

- **Project Goals**

✓ Analyze differences in usage patterns of Tigo subscribers who only use Tigo voice services, and those who adopt and use Tigo Cash

✓ *Identify likely adopters and active users of Tigo Cash*

- **Data**

✓ Six months of Call Detail Records, SMS records, and Tigo Cash records

- **Methods**

✓ Statistical and econometric analysis used to isolate key differences between different types of Tigo subscribers

✓ Supervised machine learning models used to accurately predict, based only on Call and SMS records, whether a subscriber will use Tigo Cash

- **Results**

✓ "Conversion Scores" are assigned to each of 4.5 million Tigo voice subscribers, indicating the likelihood of becoming a Tigo Cash user

✓ Using cross-validation, results are up to 86% accurate

Tigo Cash, Methodology

“Training” and “Testing” samples drawn randomly from full subscriber population

- 25,000 Voice Only: Voice subscribers who have never used Tigo Cash
- 25,000 Active Tigo Cash: Subscribers who use TC at least once in each of 6 months
- 25,000 Tigo Cash: Subscribers who have used Tigo Cash, but not every month

Feature generation: several hundred statistics measured using voice and SMS data

- Voice use: total calls, incoming vs. outgoing calls, consistent vs. sporadic users, …
- Other CDR metrics: SMS use, solutions use, data use, reload use, …
- Network and mobility: number of unique towers visited, number of unique contacts, …

Feature selection and statistical analysis

- T-tests, regressions, and recursive feature elimination used to identify which of the above metrics are most predictive of user type

Prediction and “Conversion Score” calculation

- Machine learning models used to predict user type
- Models developed on “Training” sample; accuracy calculated on “Testing” sample
- Best model is used to compute a “conversion score” to Tigo Cash and Active Tigo Cash for all 4.5 million subscribers.

Overlay RCT?

How important is the list of input features?

Performance of logistic regression classifier for variable number of features

- Significant performance gains are realized for the first 10-15 features, after which only modest improvements result from additional features

In a nutshell….

- It remains costly to provide financial services to the poor
- Commercial microfinance is unlikely to be well suited to reaching the poorest
- Subsidy will continue to play a role, and could be allocated in a more pro-poor way
- Modest benefits of microcredit so far, but there are reasons for that
- Encouraging signs for other forms of microfinance beyond credit
- Plenty for researchers to continue working on