EFFECTS OF MOBILE BANKING ON MICROFINANCE INSTITUTION PERFORMANCE IN KENYA

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Effects of Mobile Banking on Microfinance Institution Performance in Kenya

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Abstract

Mobile banking promises to increase the efficiency and outreach of microfinance loans in developing countries. The potential for microfinance institutions (MFIs) to offer their clients the ability to repay loans from any location and to receive timely loan reminders has generated widespread excitement among development practitioners and microfinance institutions. Mobile banking could mean deeper outreach to poorer and more rural people, efficiency in operation that allows for lowering the cost of loans, and higher repayment rates as clients can receive payment reminders via SMS and then repay loans from anywhere they have cell phone reception. Yet, to date there has been no quantitative test of the correlation between microfinance performance and mobile banking.

My paper appears to be the first regression-based study looking at the intersection between microfinance performance and mobile banking instituted at the MFI level. Through ordinary least squares regressions analysis I examine the effect that mobile banking has on the microfinance institutions in Kenya. My results suggest that mobile banking has no significant effect on loan repayment. The results, however, show statistically significant effects that raise the cost of personnel and of operating MFIs. Mobile banking is also related to MFIs with a deeper outreach level, as measured by average loan balance per borrower.
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INTRODUCTION

This project is a quantitative study that explores key performance variables from microfinance institutions (MFIs) that offer mobile banking as compared to those MFIs that do not. In this project, I use panel data from 25 MFIs in Kenya and I hypothesize that MFIs use of mobile banking improves MFI performance. More specifically, I hypothesize that MFIs that offer mobile banking services to their customers will also have on average more borrowers per staff members, a lower percentage of portfolio 30 days past due, and an outreach level that reaches and serves more poor clients.

Examining the link between mobile banking and MFI quality is important because mobile banking, a leapfrog technology that is often touted as the future of MFIs, may allow banks to reach more people with lower fees and interest rates.

Individuals all over the developing world have used loans from MFIs as a stepping stone to investing in their small businesses to create a better future for themselves (Abraham, 2007; Donner, 2008; Guatam, 2011). Other people have used MFIs as a vehicle through which they can smooth their income flows: saving when times are good, and spending their savings when their earnings may not be as strong. MFIs offer financial options to people who were previously unbanked.

MFIs have a problem of accessibility. Though MFIs have reached a wider audience than traditional banks, the cost of reaching even more people can be prohibitive. MFI loan officers can only administer so many loans at a time, but these loan values are much lower than traditional loans, meaning that to cover costs of operations, the interest rates they charge clients must be higher than a traditional bank charges. The poorest potential clients may also live out of reach of an MFI branch, and therefore not have access to microloans. The automation of mobile
banking could increase MFI efficiency and the accessibility of loans to a broader, more poor or rural, clientele.

Mobile banking has been around in some countries for almost a decade now, since 2001 in the Philippines and 2003 in Kenya. Researchers have performed many case studies discussing the social and organizational benefits of mobile banking when utilized by MFIs (Hinson, 2011; Vodafone, 2011). However, it is time to do a quantitative study that investigates the use of mobile banking in MFIs; and this thesis fills that gap.

**Exploring the correlation between mobile banking and higher performing MFIs**

The expected correlation of mobile banking availability and higher performing MFIs could be explained through various paths. First, mobile banking could lower the transaction costs of repaying loans, meaning that poor people are more easily able to make payments. Lower transaction costs arise from mobile banking, as clients won’t have to travel to branches to make payments, which saves them time and income. Mobile banking could also reduce the need for bank branch staff; thus increasing bank efficiency,

If payments are made and tracked electronically through mobile banking, this could increase staff efficiency. One loan officer could do more than before using this capability. Thus mobile banking used by MFIs could increase client to staff ratios, lower cost per loan made, and increase the number and broaden the target market of clients the MFI can reach.

Lower account delinquency could also be an outcome of MFIs adopting mobile banking. More convenient payment options could also result in less loan delinquency, and also increase outreach to more rural (usually poorer) clients. Mobile technology can also be used by MFIs to send repayment reminders, which would help with portfolio quality measures.
Organization of the paper

The paper proceeds with a review of literature relevant to mobile technologies in microfinance. The third section describes the general model, data sources, each variable I use in the project, and data limitations. I then discuss in the fourth section the results, and in the fifth section the policy implications of this project before providing concluding remarks in the sixth section.
BACKGROUND AND LITERATURE REVIEW

History and background of microfinance

Realizing microfinance’s prominent role in development validates the importance of studying how mobile banking might improve microfinance. Microfinance is a term for financial services that are provided to poor people, and is most commonly associated with microloans, but can include savings accounts, insurance, and other financial services. Traditional banks, as opposed to MFIs, make loans, but many poor people were unable to get loans from banks, as banks generally do not loan in the small amounts that a poor person could afford. Traditional banks do not offer smaller sized loans due to the higher cost of managing the loan per dollar lent. Thus, millions of poor people worldwide were unable to get loans from financial institutions and were left completely without financial services. In 1974, Mohammed Yunus, who is commonly recognized of the founder of microfinance, gave a loan of $27 to a group of villagers, and they successfully repaid him, and an idea and a movement was born in order to fill the gap of access to financial services (Perkins, 2008).

The idea of microfinance is that access to small loans that poor people can afford to pay off can help them escape from poverty as they use the loans to invest in small businesses and then generate income for themselves. Another function of microfinance is to help poor people smooth their income, by saving or repaying loans when times are good, and borrowing when there are unexpected shocks. The benefits of microfinance are evidence through the high demand that poor people have on receiving loans. The MIX market monitors over 1100 MFIs that serve over 74 million clients who have a collective $38 billion in loans, according to the MIX Market in 2009 (Microfinance Information Exchange, 2009).
Mobile banking technology as applied to microfinance institution’s operations

Furthermore, mobile banking applications in MFIs have wide implications for the millions of people who use microfinance globally. Mobile banking can bring convenience to MFI clients. Many people first ask how mobile phones could help poor people manage their finances. Many people from developed countries conduct banking-related tasks on computers such as paying loans, receiving reminders and checking balances. In developing countries, however, many poor people may not have regular access to a computer, but may own a cellular phone, which can be purchased for as low as $20. Therefore, integrating mobile phone technology into MFI transactions utilizes a technology medium to which many poor people have easy access, thus extending the access of automated banking technology to poor people. Mobile banking technology is also helps out the MFI, as the technology automates standard financial operations, making banking both more convenient for the client, and more cost efficient for the MFI.

An MFI needs a mobile banking platform already in place before it is able to implement a mobile banking program. The absence this platform has meant that most countries lack active mobile banking systems. However, in Kenya, a private mobile company, Safaricom, launched a successful mobile money platform in 2003. As an early entry country with high participation rates, the country’s MFIs were interested in using mobile banking, and began adopting mobile banking into their MFIs service options (Kumar, 2010).

Mobile phones for development:

Mobile phoned for development papers often focus on studying portions of a populations that use mobile phones as a conduit of information that have implications for humand development indicators. Abraham (2007), for example, shows that up-to-the minute knowledge
of market prices raises the prices that fishermen in India can command for their fish. In another case, Blauw (2011) interviewed 196 heads of household in Uganda to also find that mobile technology, whether for professional or personal uses, positively benefits individuals’ economic bottom line. Blauw also makes the point that the strongest determinant in mobile phones improving individuals’ economic outcomes is simply access to mobile technology. He attributes this effect to the benefits from interaction with the medium that will provide them with pertinent information, mobile banking services, and more as they become more familiar with product operability. These papers reinforce the fact that mobile banking is occurring within the broader phenomenon of mobile technology expansion and penetration in developing countries.

**Focus on better implementation of mobile banking:**

Another set of papers focuses on how to better capture the benefits of mobile banking. A McKinsey Quarterly paper (Beshouri, 2011) offers advice for mobile service providers on how to enter the market, suggesting that they will need 15 to 20 percent of their customers to participate in order to see economic gain from the venture. The paper also suggests partnering with post offices, utility offices, and microfinance institutions, among other businesses, in order to create a relevant network and make mobile banking more persuasive to customers. McKinsey is focusing on what the private sector can do from a business point of view.

A paper by Alleman (2011) gives a short overview of the expected benefits of mobile banking; again these benefits are lower costs and higher accessibility. Interestingly, he touches on a few challenges associated with mobile banking as well: security issues, such as hacking and dealing with stolen phones; the threat of usury and how to control it; what laws will apply to mobile banking; and enforcing interoperability from above, as individual companies have little incentive to cooperate in that area. These papers serve to illustrate the complexity and promise of
the mobile banking market, but don’t directly address issues of measuring impact of mobile banking.

**Focus on Kenya’s use of mobile money:**

Kenya is on the cutting edge of mobile money with the early success and nationwide prevalence of M-PESA. M-PESA (M for mobile, pesa is Swahili for money) is the product name of a mobile phone-based money transfer service for Safaricom, which is a Vodafone affiliate.¹ There are detailed studies about the history of M-PESA and how its reach has grown so rapidly in Kenya.

Many papers from the Consultative Group to Assist the Poor (CGAP) focus on quantifying the use of mobile money in Kenya, and subsequently exploring what about Kenya allowed this growth to occur (CGAP, 2007; Rotman, 2011; CGAP Technology Program, 2007). These papers consistently point out that there are many characteristics particular to Kenya that favor mobile money and mobile banking, such as a relatively dense population as compared to neighboring countries, a permissive regulatory environment, and an existing high use of cell phones, among other factors.

In focusing on the success of mobile money in Kenya, many other countries are brought into the spotlight for comparison. Rajanish Dass (2010), for instance, uses interviews and focus group studies from two underdeveloped states of India. Dass found that in India trust is a major bottleneck in adopting mobile banking technologies.

These papers confirmed my plan to seek mobile banking and MFI data from Kenya as this country has the most developed mobile money market. My paper uses Kenyan MFIs in the analysis because Kenya is the country with MFIs that have the most experience with mobile

banking. This experience in mobile banking allows me to focus on the impact that mobile banking could have for the microfinance Industry as demonstrated by MFI performance data.

**Focus on mobile banking’s impact on MFI outreach:**

An important aspect of microfinance is that it provides financial services to people who previously had no access – this is referred to as having a broad outreach. Ron Webb (2009) comments that the main strength of branchless banking lies not in its ability to cut costs, but instead in its ability to bring banking to the people of the rural countryside, creating accessible touch points where before it was impossible – in other words through increasing outreach. Shrivastava (2011), seeking to test poor peoples’ perception of mobile banking, uses a focus group methodology to obtain the attitudes of low-income people towards mobile financial services. In her paper she concludes that due to the people’s attitudes about mobile banking, that mobile banking can indeed be a channel to reach out to low-income groups.

Guatam Ivatury (2006) of CGAP offers another survey-based approach from South Africa, where he surveyed 515 low-income people in South Africa. He found that “three hundred of those surveyed do not use m-banking [a common term for mobile banking], while 215 are customers of WIZZIT, a startup mobile banking provider.” His conclusions also deal with perceptions of mobile banking, and again, he finds that mobile banking services are valued by poor people in South Africa, and also that mobile banking is more affordable than traditional banking.

My paper also addresses the topic of outreach. As Cull (2011) states in his paper, in the MIX Market’s database, a there is no direct measure for “outreach.” Both Cull and I use the Mix

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b MIX Market is a non-governmental organization that collects and provides data on MFI social and financial performance.
Market’s database as a source. Cull mentions that there are many proxy variables that can represent outreach such as “average loan size, the fraction of borrowers that are women, and the fraction of clients living in rural areas.” I chose to use average loan balance per borrower as my proxy for outreach, as it is the variable that was very consistently reported in my dataset. Fraction of clients in rural areas was absent in my dataset, and there were not enough observations of percentage of women borrowers.

**Focus on Cost:**

Many papers make the same conclusion that although microfinance serves the poor, high loan costs (which are necessitated by the higher transaction cost per loan amount ratios) are often a barrier, and technology can be a tool in lowering those transaction costs (Hinson, 2011). One paper (Kumar, 2011) goes further and not only suggests that this may be the case, but shows through a case study that costs actually have been lowered for a specific MFI that utilized mobile banking. Kumar reports that Green Bank in the Philippines saves $16 in transaction costs over the course of a $400 loan when a customer uses mobile payments, and thus they are able to incentivize their clients to use mobile payments through offering lower interest rates for those who sign up to use mobile banking. This study shows support for the theory that when an MFI adopts mobile banking it will lower operating costs for the MFI, and these lower costs will be passed on to the customers. My paper investigates if this cost-lowering outcome is evident through a regression of data of 25 MFIs on the reported figures that MFIs have submitted to the MIX Market.

**Focus on data at the MFI level:**

In terms of methodology, Cull’s paper (2011) also analyzes performance data from the MIX Market, and his unit of analysis is the individual MFI. I supplement the MIX Market data
with information about whether each MFI in my dataset has mobile banking technology available to its clients, and if so, beginning in which year. I received this information from Jacinta Maiyo, a technical project manager at the Grameen Foundation in Kenya. The Grameen Foundation is a non-profit branch inspired by the work of the Grameen Bank in India. The Grameen Foundation has a department to support mobile financial services, and a deep commitment to learn about and study best practices for integrating mobile money technology with MFIs.

One of Cull’s findings related to what I am studying is that “if we take loan size as a proxy for the poverty of customers (smaller loans roughly imply poorer customers), microfinance banks appear to serve many customers who are substantially better-off than the customers of nongovernment organizations.” Cull was studying the outcomes for outreach of MFIs being either a non-profit organization or a regulated MFI. I will study the outcome for outreach of MFIs either having mobile banking technology or not.

To summarize, my paper is an MFI-specific investigation that encompasses mobile banking data into regression analysis along with MFI performance data. This kind of research has not been previously performed, as the specific data about mobile banking has never been aggregated and integrated with MFI performance data. I thus contribute to understanding performance outcomes associated with the implementation of mobile banking programs in MFIs.
DATA DESCRIPTION AND EMPirical MODEL

The main idea inspiring my project is that mobile banking improves MFI quality. I look for improvement in MFI performance in four areas: lower MFI operating and personnel costs, increases in staff efficiency, improved outreach to poorer clients, and improved payback rate. My investigation uses regressions with dependent variables from each of these areas of MFI performance.

The general model

MFI quality variable = f(Mobile banking available to MFI clients + MFI peer group characteristics control variables + Other MFI performance variables + Error term) (1)

This general model begins with the MFI quality variable in question. In my project I decide to examine five separate variables as dependent variables: operational costs, personnel costs, borrowers per staff member, average loan balance per borrower, and percentage of portfolio at risk for over thirty days. I then go on to see how mobile banking is associated with each of these five dependent variables. The third component of this model are the MFI peer group characteristics, which include variables such as age of the MFI, number of clients, measure of an MFI’s assets, and whether an MFI is regulated or not. The fourth set of variables consists of other MFI performance variables that may explain variation in the dependent variables. This set of variables includes return on equity, cost per borrower, and borrower per staff member. I believe this general relationship adjusts for the appropriate factors that affect MFI operations, and thus isolate the effect of mobile banking.

Sample

My sample is comprised of data from all MFIs that have reported information to the MIX market that were located in Kenya, 25 MFIs in total. The span of time is from 2005 to 2010.
giving me 96 observations. I chose to include data beginning in 2005 as the first mobile banking technologies made their debut in Kenyan MFIs at around this time. As this thesis is based upon regression analysis, there was initially concern that small sample size could be an obstacle to finding significant results. However, the results proved to be strong, with statistically significant coefficients and F statistics and R-squares of acceptable levels.

**Longitudinal data**

For analysis, I use the observations as longitudinal data, and not as panel data. Since I have only 96 observations total, using the data as panel data would have resulted in too few degrees of freedom and would have cut into my regressions’ explanatory power. As the history with mobile banking technology in Kenya becomes longer and more widespread, there will be more observations. Each year that passes offers an opportunity to bring in 25 new observations from each of the 25 MFIs in Kenya, not to mention the possibility that more MFIs may begin operations in Kenya. Thus, by October 2014, with around 50 more observations expected to be generated, the ground could be ripe for investigations using panel data.
### Table 1: Dummy variable definition and descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Number of observations</th>
<th>Total number of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mobile banking</td>
<td>0 = No mobile banking</td>
<td>66</td>
<td>96</td>
</tr>
<tr>
<td>mbanking</td>
<td>1 = Mobile banking</td>
<td>30</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0 = New (new)</td>
<td>19</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 = Young (young)</td>
<td>22</td>
<td>96</td>
</tr>
<tr>
<td></td>
<td>2 = Mature (mature)</td>
<td>55</td>
<td></td>
</tr>
<tr>
<td>Outreach</td>
<td>0 = Small (osmall)</td>
<td>36</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 = Medium (omed)</td>
<td>19</td>
<td>87</td>
</tr>
<tr>
<td></td>
<td>2 = Large (olarge)</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>Regulated</td>
<td>0 = Unregulated</td>
<td>44</td>
<td>96</td>
</tr>
<tr>
<td>regulated</td>
<td>1 = Regulated</td>
<td>52</td>
<td></td>
</tr>
<tr>
<td>Scale</td>
<td>0 = Small (ssmall)</td>
<td>37</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1 = Medium (smed)</td>
<td>27</td>
<td>95</td>
</tr>
<tr>
<td></td>
<td>2 = Large (slarge)</td>
<td>31</td>
<td></td>
</tr>
</tbody>
</table>

### Table 2: Continuous variables and descriptive statistics

<table>
<thead>
<tr>
<th>Variable and number of observations</th>
<th>Mean</th>
<th>Median</th>
<th>Standard Deviation</th>
<th>Min</th>
<th>Max</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets</td>
<td>93</td>
<td>$87,000,000</td>
<td>$6,500,000</td>
<td>$250,000,000</td>
<td>$1,493</td>
<td>$1.7</td>
</tr>
<tr>
<td>Average loan balance/borrower</td>
<td>79</td>
<td>$339.25</td>
<td>$293.35</td>
<td>$278.52</td>
<td>$9.29</td>
<td>$1197.50</td>
</tr>
<tr>
<td>Borrowers per staff member</td>
<td>78</td>
<td>177.59</td>
<td>137.60</td>
<td>116.90</td>
<td>9.00</td>
<td>673.08</td>
</tr>
<tr>
<td>Cost per borrower</td>
<td>66</td>
<td>102.40</td>
<td>81.08</td>
<td>79.18</td>
<td>3.57</td>
<td>390.12</td>
</tr>
<tr>
<td>Operating expense to asset ratio</td>
<td>84</td>
<td>0.20</td>
<td>0.16</td>
<td>0.13</td>
<td>0.06</td>
<td>1.08</td>
</tr>
<tr>
<td>Operating expense/loan portfolio</td>
<td>79</td>
<td>0.33</td>
<td>0.26</td>
<td>0.23</td>
<td>0.04</td>
<td>1.91</td>
</tr>
<tr>
<td>Personnel</td>
<td>86</td>
<td>486.24</td>
<td>109</td>
<td>925.47</td>
<td>2</td>
<td>5563</td>
</tr>
<tr>
<td>Personnel expense/loan portfolio</td>
<td>63</td>
<td>0.16</td>
<td>0.13</td>
<td>0.10</td>
<td>0.02</td>
<td>0.41</td>
</tr>
<tr>
<td>Portfolio at risk &gt; 30 days</td>
<td>74</td>
<td>0.10</td>
<td>0.09</td>
<td>0.08</td>
<td>0.00</td>
<td>0.37</td>
</tr>
<tr>
<td>Return on equity</td>
<td>83</td>
<td>.11</td>
<td>0.08</td>
<td>.42</td>
<td>-0.81</td>
<td>1.86</td>
</tr>
</tbody>
</table>
Variables

Dependent Variables:

I use five different dependent variables to examine the effect that mobile banking has on each of those variables. They are: MFI operation costs, MFI personnel costs, borrowers per staff member, average loan balance per borrower, and portfolio at risk for more than thirty days. Here I list the five equations I estimate, and I go into each equation in turn in the five subsections that follow.

\[ Op exploa = \beta_0 + \beta_1 (mobile\ banking) + \beta_2 (new) + \beta_3 (young) + \beta_4 (omed) + \beta_5 (small) + \beta_6 (pers) + \beta_7 (regulated) + \beta_8 (roe) + \beta_9 (smed) + \beta_{10} (ssmall) + \beta_{11} (borperst) + \varepsilon \]  

(2)

\[ Per exploa = \beta_0 + \beta_1 (mobile\ banking) + \beta_2 (new) + \beta_3 (young) + \beta_4 (omed) + \beta_5 (small) + \beta_6 (pers) + \beta_7 (regulated) + \beta_8 (roe) + \beta_9 (smed) + \beta_{10} (ssmall) + \beta_{11} (borperst) + \varepsilon \]  

(3)

\[ Bor perst = \beta_0 + \beta_1 (mobile\ banking) + \beta_2 (new) + \beta_3 (young) + \beta_4 (omed) + \beta_5 (small) + \beta_6 (pers) + \beta_7 (regulated) + \beta_8 (roe) + \beta_9 (smed) + \beta_{10} (ssmall) + \varepsilon \]  

(4)

\[ Avg loan balb = \beta_0 + \beta_1 (mobile\ banking) + \beta_2 (omed) + \beta_3 (small) + \beta_4 (roe) + \beta_5 (assets) + \beta_6 (costperbor) + \varepsilon \]  

(5)

\[ Port 30 = \beta_0 + \beta_1 (mobile\ banking) + \beta_2 (new) + \beta_3 (small) + \beta_4 (regulated) + \beta_5 (roe) + \beta_6 (ssmall) + \beta_7 (costperbor) + \varepsilon \]  

(6)

Cost variables

Operating Expense / Loan Portfolio (%)\(^c\) (op exploa) – Equation 2

This variable is defined as total operating expenses recorded by microfinance organizations divided by the total value of the loan portfolio. This variable is one of the dependent variables. I expect mobile banking to lower operating expenses through increased staff productivity, and therefore to have a negative correlation with operating expenses.

\(^c\) Loan portfolio is the total value of all loans held by a given microfinance institution.
Personnel Operating Expense / Loan Portfolio (%) (opexploa) – Equation 3

Personnel operating expense per loan portfolio is one of the dependent variables. I expect mobile banking to lower personnel expenses through increased staff productivity, and therefore to have a negative correlation with personnel expenses.

Staff efficiency variable

Borrowers per Staff Member (borperst) - Equation 4

This variable is another of the dependent variables. I expect mobile banking to be positively correlated with borrowers per staff member, because by using automation for mobile loan payments, the number of borrowers a staff member can manage should increase.

Outreach variable

Average loan balance per borrower (avgloanbalb) – Equation 5

This is another dependent variable. This is measured by taking the amount of money owed to the MFI and dividing it by the number of borrowers at the MFI. A smaller average loan balance per borrower indicates that smaller loans have been made, implying that poorer clients have been served. I expect mobile banking will be especially helpful in reaching out to the poorer clients, and therefore mobile banking will be negatively correlated with average loan balance per borrower.

Repayment variable

Portfolio at Risk > 30 days Ratio (%) (port30) - Equation 6

This is the final dependent variable. The portfolio at risk variable is calculated by value of all loans outstanding that have one or more payment overdue for more than 30 days. This includes the entire unpaid principal balance, including both the past due and future
installments, but not accrued interest. Then that amount is divided by the total value of the loan portfolio to get a percentage measure of the portfolio at risk. I expect that mobile banking should be correlated with a higher rate of repayment, and thus a lower portfolio at risk ratio. This increase in portfolio quality would be attributable to mobile banking because repaying loans will be easier as repayment can be made anywhere there is mobile phone connectivity, and also as mobile technology can also be configured to send loan repayment reminders to borrowers.

Test variable

Mobile Banking (mbanking) -

Whether or not an MFI offers mobile banking services to its clients or not is the test variable, which is an indicator equal to one if the MFI offers mobile banking to its clients and equal to zero if mobile banking is not available. If mobile banking is correlated with any differences in MFIs, then the coefficient will be absolutely and statistically significantly larger than zero. Jacinta Maiyo of the Grameen Foundation provided me MFI-level data concerning mobile banking technologies for each year from 2005 to 2010 as to which of the 25 MFIs in Kenya were offering it. I predict that mobile banking will be positively correlated with borrowers per staff, and negatively correlated with the percentage of loan portfolio at risk, average loan size, personnel expense per loan, operating expense per loan.

MFI peer group variables

The MIX market collects qualitative data from MFIs that helps categorize the MFIs by size, outreach, legal status, and more. For my purposes, these data are highly useful control variables, and are explained in detail below.
Age (*new, young, mature*) –

This ordinal variable reports on the number of years the MFI has been in existence. New (0 in the dataset) is 1-4 years, Young (1 in the dataset) is 5-8, and Mature (2 in the dataset) is 8 years and above. I would expect that older MFIs might have a larger client base, be more financially sustainable and stable, thus having lower operating and personnel costs per loan portfolio, as well as better loan repayment rates, and more borrowers per staff member, due to optimization of lending practices. Thus the age of an MFI would be positively correlated with borrowers per staff member and negatively correlated with percentage of loan portfolio at risk, personnel costs, operating costs. I do not expect a strong correlation between age of an MFI and average loan balance per borrower, as I believe the target market of an MFI is not dependent on and does not change based on the years and MFI has been in existence.

Regulated or unregulated (*regulated*) –

This is a simple dummy variable that is equal to one if an MFI is regulated, and is equal to zero if the MFI is not regulated. This may be an important variable to control for, as regulated MFIs have to comply with higher levels of external monitoring and reporting than unregulated MFIs. Regulation could lead an MFI to have higher operating costs due to costs of compliance, and lower borrower per staff member ratios due to regulations trying to encourage quality service. Regulated MFIs are often seen as more savvy and transparent, as these qualities are necessary to meet reporting requirements. I estimate a positive relationship between MFI regulation and operational expense per loan and personnel expense per loan. I also expect a negative relationship between regulation and borrowers per staff member.
Scale (ssmall, smed, slarge) –

This ordinal variable classifies the size of an MFI based on the value of all the gross loan portfolios. A large scale MFI (2 in the database) has more than $8 million USD in value, a mid scale (1 in the database) has between $2 million and $8 million, while a small scale MFI (0 in the database) has less than $2 million in its portfolio. It is a general control variable, and I might expect to see it negatively correlated with operating and personnel costs per portfolio, as a larger bank would have achieved economies of scale. I would expect also that smaller scale MFIs would have a better record for repayment rates, with less of their portfolio at risk, as a smaller MFI may be more likely to better know their clients, and therefore better work with them for repayment.

Assets (assets) –

This variable is the total of all net asset accounts. With this variable I seek to control for the financial size of the MFI. It is a general control variable, and I might expect to see it negatively correlated with operating and personnel expense per loan due to economies of scale. Other relationships between assets and dependent variables do not seem to have a theoretical base for me to estimate the direction of their possible relationships.

Number of Personnel (pers) –

With this variable I seek to control for the size of the MFI as demonstrated through its number of employees. It is a general control variable, and I might expect to see it negatively correlated with operating and personnel expense per loan due to economies of scale. Other relationships between the number of personnel and dependent variables do not seem to have a theoretical base for me to estimate the direction of their possible relationships.
Outreach (*osmall, omed, olarge*) –

This is an ordinal variable that classifies MFIs into three groups based on how many borrowers the MFI serves. A large outreach (2 in the dataset) is 30,000 or more borrowers, medium (1 in the dataset) is 10,000 to 30,000, and a small outreach (0 in the dataset) is fewer than 10,000. I might expect to see outreach negatively correlated with operating and personnel expense per loan due to economies of scale. Other relationships between the size of client base and dependent variables do not seem to have a theoretical base for me to estimate the direction of their possible relationships.

**Other MFI Performance Variables**

**Cost per Borrower (costperbor)** -

Cost per borrower is defined as the operating expense divided by the number of active borrowers. This variable could be correlated negatively with average loan balance per borrowers, because when loan balances are smaller, then in general it costs more to manage them. I would expect cost per borrower to have a positive correlation with percentage of portfolio at risk for more than thirty days, as an MFI that has higher operation costs per borrower probably pass those higher costs down to the client, and therefore the client has a more difficult time paying off their higher cost loan. I expect cost per borrower to have a negative correlation with average loan balance per borrower, as MFIs that manage many smaller loans have higher operating costs per borrower than MFIs that manage the same amount of money for a fewer number of larger size loans. Due to the very high correlation between cost per borrower and operating expense per loan and personnel expense per loan, I do not include cost per borrower in equations one and two.
Return on Equity \((\text{roe})\) –

Return on equity is the net operating income, less taxes, divided by equity. This variable illustrates the financial success of MFIs, and can help explain various dependent variables I am testing. An MFI with a higher ROE most likely has lower operating and personnel costs, and therefore I expect a negative correlation between ROE and cost variables. ROE also may be positively correlated with average loan balances per borrower, as when a loan size is larger, it is generally given to a wealthier client, and therefore a larger loan has a better chance of repayment. Consequently, when serving a wealthier market with larger loans, an MFI could loan more money, and bring in more income for the same amount of equity.

Borrowers per staff member \((\text{borperst})\)

Borrowers per staff member is used in equation three as a dependent variable, but also in equations one and two as an independent variable that explains variation in operating expense and personnel expense per total loan portfolio. When used as an independent variable, I expect that borrowers per staff has a negative relationship with operating expense and personnel expense per total loan portfolio because if there are more borrowers per staff member, the staff member is overall being more productive and costing less money per client managed. I would also expect a negative relationship between borrower per staff member and percentage of loan portfolio at risk for greater than thirty days, as a staff member with fewer clients to manage can spend more time following up with various clients to pressure them to pay, thus bringing about lower portfolio at risk rates.
Data limitations

As in every quantitative project, there are limitations to the data. In my particular project I am using information on MFIs that only tells me whether the MFI offers mobile banking or not. I have no measures of the depth of mobile banking usage from each MFI. For instance, I do not have data on how many clients or what ratio of clients in a given MFI make payments via mobile phones, or how many clients receive loan repayment reminders via text.

Another concern that could affect results is the newness of mobile banking with MFIs. There are only seven MFIs in my data set that have had mobile banking programs for more than two years. The benefits from mobile banking could take time to accrue, as the first couple of years the MFI invests many resources in getting the program to function. More time is then needed to work out the kinks of a new program, and to encourage clients to use the new mobile banking services. As the programs are so new, benefits might not be showing up in performance data, and therefore may not show up in my results.

A third concern is that mobile banking adoption by MFIs could be a highly correlated with high-performing MFIs in the first place. Perhaps only high performing MFIs offer mobile banking. To correct for this problem, I would need to perform instrumental variable regressions, but I lack both the variables for this, and the observations to support it. I discuss this issue further in the final section. I now turn to the results of my estimators.
RESULTS

The equations I estimate investigate the effects of an MFI having a mobile banking program on a variety of performance variables that are interesting to policy makers; areas in which one would hope or expect mobile banking to make a contribution: cost reduction, increased staff efficiency, outreach, and decreased loan at risk rates. In this investigation I examine the relationship between mobile banking programs and ten dependent variables in separate regressions. From these ten regressions, I chose the five regressions that showed the greatest power in explaining variation in the dependent variables and in which mobile banking played a statistically significant role. Regression results are in Table 3 on page 26. In the section below I fully discuss these regressions.

Mobile Banking and Operating Costs: Operating expense per loan portfolio

I investigate expense per loan portfolio as the dependent variable of interest when looking at the effect that mobile banking has on costs. At the end of the day, one hopes that the efficiency gains that mobile banking will show up in lower operating costs. Operating costs are different than total costs, and include only expenses related to operations, including all personnel expense, depreciation and amortization, and administrative expense. This measure therefore is appropriate, as it does not include the costs, for example, of building brick and mortar offices, which would be a cost that mobile banking would not directly influence.

Regression two explains 56.39% of the variation in the operating expense per loan portfolio ratio. The F-Statistic, which describes the overall significance of the model, is 25.96, which is statistically significant at all confidence levels (Prob >F = 0.0000).

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*d* See appendix for a listing of all 10 dependent variables that I considered.
In regression two, mobile banking has a statistically significant and positive correlation with operating expense per loan portfolio. All else equal, a bank that has a mobile banking program is associated with a 8.7 percentage point rise in operating expense per loan portfolio (p < 0.0005). Operating expense per loan is a number expressed as a percentage, and therefore if an MFI has an operating expense per loan ratio of 0.33 (the average ratio), it is estimated if there is a mobile banking program that this ratio rises to 0.417, which is a substantial increase. This is opposite of what would be hypothesized by a theory claiming that mobile banking helps MFIs manage more loans with less effort. This result could be explained as MFIs that have invested more heavily in mobile bank programs have used some of their assets in this investment, thus increasing their operating cost through administrative expenses. The cost-saving benefits from mobile banking may also occur once a mobile banking program is more mature and more deeply adopted by the clientele; both would take time to see in the results.

Now I turn to the control variables. Both new and young MFIs show point estimates for higher operating expenses, with coefficients of 0.173 (p = 0.122) and 0.100 (p = 0.03), respectively. These higher operating costs per loan portfolio for new and young MFIs could be explained because younger MFIs are still learning to run efficiently, and therefore have higher operating costs than the mature institutions.

Outreach levels also prove to be a significant variable in explaining variation in operating expense per loan portfolio. When comparing MFIs with a large outreach (30,000+ borrowers) to medium outreach MFIs (10,000-30,000 borrowers), medium outreach MFIs have a 11.7 percentage point higher operating expense per loan portfolio (p = 0.002) than large outreach MFIs, and small outreach MFIs (<10,000 borrowers) have a 13.6 percentage point higher operation expense per loan portfolio (p < 0.011) than large outreach MFIs. This points to the
relationship that small outreach MFIs, when compared with large-outreach MFIs, have higher operational costs to loan portfolio size. These results could indicate economies of scale in managing loans that large-outreach MFIs take advantage of that smaller outreach MFIs don’t have access to.

Regulated MFIs are associated with a 12 percentage point increase in the operation expense per loan portfolio ratio ($p = 0.001$). This coefficient illustrates the broadly known theory that higher costs are associated with being a regulated MFI that is discussed in existing literature (World Bank, 2009).

Borrowers per staff member and number of personnel have statistically significant but very small magnitude effects. I have included these variables in the regression, however, as they indicate statistically significant effects, although these effects are not of large magnitude. The near zero coefficient of borrowers per staff member is interesting considering that traditional microfinance lending can be quite labor intensive, and labor costs are included in operating costs, thus pointing towards an expected negative relationship with the operating expense per loan portfolio ratio. The near zero coefficient of number of personnel members is also interesting, considering that larger outreach MFIs (thus those with necessarily larger personnel numbers to serve those clients) has a negative relationship with the operating expense per loan portfolio ratio. Perhaps the relevance that number of personnel has for the ratio is explained by the outreach control variables in the model with which number of personnel is correlated.

Mobile banking and staff efficiency: Personnel expense per loan portfolio ratio

Related to the expense per loan portfolio ratio is the personnel expense per loan portfolio ratio. This cost variable captures the variation in costs of personnel, which is the area of expenses that I would expect for mobile banking to have the most opportunity to affect through increasing
the ability of staff to serve more clients. This variable is also a type of cost variable, yet also represents a measure of staff efficiency, as a staff that can service the same size of a portfolio at a lower price may be argued to be more efficient.

Regression three explains 68.12% of the variation in the operating expense per loan portfolio ratio. The F-Statistic, which describes the overall significance of the model, is 15.32, which is statistically significant at all confidence levels (Prob >F = 0.0000).

Specifically of interest then, is the mobile banking coefficient. If an MFI has a mobile banking program it is likely to have a personnel expense per loan portfolio ratio that is 6.9 percentage points higher than MFIs with no mobile banking program (p = 0.001). Again, this increase in costs can be explained by up-front expenses with hiring personnel to build, implement, and manage the necessary information technology associated with mobile banking.
### Table 3: Regression results for MFI performance variables†

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<tr>
<th></th>
<th>2 opexploa</th>
<th>3 persexploa</th>
<th>4 borperst</th>
<th>5 avgloanbalb</th>
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$p < .05\,*$,  $p < .01\,**$,  $p < .001\,***$

$t$ statistics in parentheses

† Each column represents a unique regression, and not all independent variables were used in each regression. The blanks in a given column mean that a given variable was not used in the regression. Variables were omitted when they were insignificant and did not contribute much to the explanatory power of a given model.
Many of the variables in the personnel expense per loan portfolio regression (from here on referred to as regression three) are similar in direction and relative magnitude as the variables in regression two. Being a new MFI has similar effects on the personnel expense per loan portfolio ratio [coefficient of .125, (p = 0.001)] as it had for the operating expense per loan portfolio ratio [coefficient of 0.173 (p=0.022)]. This is an expected result, as personnel expenses are a part of operating expenses, so these two variables should be highly correlated to each other, and thus the models very similar. The return on equity, borrowers per staff, and number of personnel coefficients in regression three also are similar to the estimates in regression two, with statistically significant but very small magnitude effects.

Two other coefficients in regression two are also significant and the same in sign as in regression two. The coefficient for a regulated bank is 0.114 (p < 0.0005) in regression three while it is 0.120 (p = 0.001) in regression two. Similarly, the coefficient for mobile banking in regression two, 0.871 (p < 0.0005) is similar in magnitude to the coefficient in regression three, 0.069 (p = 0.001). The similar results from these two regressions are essentially showing the same story. This is because personnel expenses are a subset of operating expenses, and therefore the personnel expense per loan portfolio measurements are correlated and smaller than operating expense per loan portfolio measurements. Therefore a larger coefficient for operating expense per loan portfolio ratio is analogous to a smaller coefficient for personnel expense per loan portfolio.
Mobile banking and staff efficiency: Borrowers per staff

Regression four explains 42.17% of the variation in borrowers per staff members. The F-statistic, which describes the overall significance of the model, is 5.07, which is statistically significant at all confidence levels (Prob > F = 0.0000).

Examining the relationship between mobile banking and the measure of borrowers per staff member, on average an MFI with a mobile banking program is associated with about 45.384 fewer borrowers per staff member (p =0.047). This finding is opposite of the expected relationship that mobile banking would allow loan officers, which make up a substantial portion of an MFI’s staff, to take on more borrowers due to enhanced ease at collecting loans and communicating with clients via SMS. However, this finding could be explained as microfinance organizations that are implementing projects in mobile banking need to hire personnel to build and manage the mobile banking information technology, which increases the number of staff members while not immediately increasing the number of borrowers, or increasing staff more quickly than borrowers, at least at first.

The age of the MFI was associated with borrower per staff measures. When compared to mature MFIs (aged 8 years and more), the new MFIs (aged 1-4 years) have on average 182.614 (p =0.008) more borrowers per staff, and the young MFIs (aged 4-8 years) have on average 55.027 (p = 0.029) more borrowers per staff. These results could be explained as perhaps new MFIs are using on average a different business model than more mature MFIs. Maybe relatively staff-intensive village bank and group lending methods were more popular among MFIs that were founded eight or more years ago, and the younger MFIs are focusing on maximizing the number of clients served.
The number of clients that an MFI serves is also associated with borrower per staff measures, with MFIs that have a small client base having on average 210.86 fewer borrowers per staff members ($p = 0.003$), and those with a medium client base having on average 119.13 fewer borrowers per staff member ($p = 0.043$) than MFIs with a large client base. This could be because MFIs with small client bases may organize themselves to have more personalized outreach, which would limit the ultimate size of their outreach, and therefore be associated with a smaller client base. There could also be an economy of scale such that as the number of clients increases, the number of administrators stays at a similar level or needs to increase at a lower rate, thus allowing larger MFIs to have a lower borrower per staff measure.

Conversely, the number of personnel a bank has is not strongly correlated with the borrowers per staff measure, showing a small magnitude coefficient that is not significant at standard levels. This is interesting, however, as the number of personnel is expected to be correlated with the number of clients served, and thus to have a positive correlation with borrowers per staff measures. Overall portfolio size and ROE are also not strongly correlated with borrower per staff. I include these two variables, however, as it helps bring out the significance of the other variables, contributing to the fit of the model.

**Mobile banking and outreach: Average loan balance per borrower**

The average loan balance per borrower is the measure I chose to represent outreach. In the microfinance field there is the idea of the double bottom line, which is that MFIs should care both about financial sustainability of their operations, as well as about reaching those in need of financial services. In other words, MFIs are concerned about their depth of outreach, described as reaching the previously not served, which are more often the very poor, the rural clients, or women (Lafourcade, 2005). In the MIX Market data set, there were a few variables in addition
to average loan balance per borrower that might be used to represent outreach. One is the percentage of borrowers who are women, with the higher percentages being associated with deeper outreach. However, I could not use this variable as it was only reported 68 times, thus limiting the sample size in the whole regression.

There is also a “target market” variable, which is based on the range of loan sizes a bank tends to make. This variable only has three categories, and so is not optimal for use as a dependent variable in the regressions. However, instead of using this “target market” variable, it was possible to go straight to the measure from where target market was derived: the average loan balance per borrower, which is a continuous variable, and useful for regression. Wealthier clients take out larger loans on average, thus average loan balance per borrower serves as a good measure of MFI outreach to poor clients.

Regression five explains 81.14% of the variation in the average loan balance per borrower. The F-Statistic, which describes the overall significance of the model, is 103.24 which is statistically significant at all confidence levels (Prob >F = 0.0000).

Mobile banking has a negative correlation with average loan balance per depositor. On average an MFI with a mobile banking program has an average loan balance per depositor of $158.61 less (p = 0.027) than an MFI with no mobile banking technology. This finding is encouraging as perhaps mobile banking technology is active in MFIs whose clients are poorer. Ultimately, I hope the one goal of mobile banking is to reach out to the poorest of people, and perhaps this result shows that it is possible for mobile banking to reach the poorest clients.

Size of client base has a strong and significant relationship with average loan balance per depositor. Small and medium MFIs have significantly smaller average loan balances per depositor than larger MFIs; $241.34 (p < 0.0005) and $194.59 (p = 0.002) smaller average loan
balances, respectively. These results are expected because smaller MFIs are often more tied to their mission of serving the poor, and because it is more difficult for a mobile bank to be profitable enough to reach a large scale without seeking clients who can afford to receive larger loans.

Cost per borrower has a statistically significant ($p < 0.0005$) positive relationship with borrowers per staff ratio. Each $1$ rise in the cost per borrower measure is associated with an increase of $3.31$ of the average loan balance. To put this in perspective, I compare the expected average loan balance per borrower of the MFI with the lowest cost per borrower to the MFI with the highest cost per borrower in our dataset. The MFI with the highest cost per borrower is estimated to have $1279.48$ higher average loan balance per borrower than the MFI with the lowest cost per borrower. This relationship is not expected as it costs less money to manage larger loans.

Assets have a highly significant ($p < 0.0005$) but small magnitude coefficient ($4.68 \times 10^{-7}$). However, including this variable in the model is important to avoid omitted variable bias.

**Mobile banking and loan repayment: Portfolio at risk greater than thirty days**

Regression six explains $32.31\%$ of the variation in portfolio at risk for greater than thirty days. The F-Statistic, which describes the overall significance of the model, is $10.41$, which is statistically significant at all confidence levels ($\text{Prob >F} = 0.0000$).

Portfolio at risk for greater than thirty days is a measure of portfolio quality. I expect that mobile banking should be associated with a lower amount of portfolio at risk because loan repayment reminders can be sent to clients, and clients can make loan payments via text message. However, when I investigated a model to show the relationship between mobile banking and portfolio at risk, I found a very small and insignificant negative effect ($p = 0.437$)
for mobile banking. Interestingly enough, however, other variables in the model have significant relationships to portfolio at risk measurements. An organization with a small client base has on average a 9.4 percentage point lower portfolio at risk (p < .0005) when compared to medium and large sized MFIs. This can perhaps be explained by the more personal client attention that may be given at a smaller MFI, so the smaller feel to the organization may encourage a client to repay on time. Or perhaps smaller MFIs are more selective with whom they make loans, and the size of the loans, due to the greater relative risk of any one loan for a smaller MFI.

Banks with a small portfolio size have a higher portfolio at risk rate: 9 percentage points higher on average (p = 0.001). This is interesting, and conflicts with what is expected based on the coefficient for small client base MFIs (osmall) already shown in the model. Due to the apparent correlation of these two control variables – which is that banks with fewer clients (osmall) should have smaller total portfolios (ssmall) - it is expected that small portfolio MFIs (ssmall) would have the same effect on portfolio at risk as small client bases (osmall); however this is not the case. MFIs with a smaller client base have a negative relationship with percentage of portfolio at risk, while MFIs with small portfolio size (ssmall) have a positive correlation. I do not have a good explanation for this result, so it bears further study.

Regulated MFIs on average have a 6.23 percentage point lower portfolio at risk rate (p = 0.001) than unregulated banks. Perhaps this is because regulated MFIs comply with higher operating standards that lead to more prudent loaning practices.

Two variables have small magnitude yet statistically significant coefficients, and are thus included in the model to clarify relationships between other variables. ROE has a small magnitude yet significant coefficient: a 5.23 percentage points lower portfolio at risk measure.
per each 100% increase in ROE (p = 0.017). Average loan balance per borrower has a coefficient of 0.00015 (p < 0.0005).

I now turn to policy implications and conclusions.
**Policy Implications**

In this paper I set out to examine the relationship between mobile banking programs and differences in MFI performance variables. I gathered information about the years for which mobile banking programs were instituted by 25 microfinance institutions in Kenya, the developing country with the most advanced usage of mobile banking. I then merged this mobile banking information with performance data available from the MIX Market. With the data set complete, I performed OLS regression with mobile banking as the test variable to seek statistically significant relationships between mobile banking and key performance variables. I found that mobile banking is associated with higher operating expenses per total loan portfolio of the MFI, higher personnel expense per total loan portfolio of the MFI, a lower number of borrowers per staff member, and a lower average loan balance. Below I expound upon how these results can inform policy including suggestions for individual MFIs and for the national governments that help create regulatory environments for MFIs.

*Mobile banking and operating and personnel costs*

At first glance, it could appear that mobile banking programs simply raise the operating costs of mobile banks. However, before throwing out the idea that mobile banking can bring more efficiency and lower operating costs to MFIs, I will tease out the likely relationship between mobile banking and operating and personnel costs before making policy suggestions. First of all, any rise of cost associated with instituting and managing a mobile banking program may be exaggerated by the fact that mobile bank programs are very new and there are up front costs that the MFI must incur now, but these program start-up costs will not be so high once the
infrastructure is in place, computers have been bought, and staff members have been trained. Many of these costs are high at the beginning of programs, but fall over time.

Another reason that the association of mobile banking programs with higher MFI operating and personnel costs may be overstated relative to the medium to long run is also related to the newness of the mobile banking programs. In my sample only seven of eleven MFIs with mobile banking programs were instituted in or before 2008, and none before 2005. As mobile banking is a new or young program in many observations in this data set, a high percentage of clients may not yet use the mobile banking technology, as it will take time for clients to adapt the new technology. Thus, any cost reductions that could result from increases in efficiency in managing loans might be limited until there is more widespread use of mobile banking that will come with the maturation of mobile banking programs and adaptation by users.

With new technology and products there is a product adoption life cycle, where at first few use a product, and then as time goes by, more people embrace the new product or service. Due to its newness, mobile banking for microfinance purposes is on the early end of the adoption curve, and in the future more clients will continue to adapt to mobile banking and that these efficiencies will be reached. Also, costs will come down with increased implementation. So for these three reasons, I expect benefits of mobile banking to be realized more fully in the next couple of years that come. Therefore, the results of higher costs should not deter MFIs from implementing mobile banking programs, but instead should give impetus for MFIs with mobile banking programs to double up on their efforts to encourage clients to use the service.

**Mobile banking and borrower per staff ratios**

The negative relationship between MFIs with mobile banking and borrowers per staff member can be explained, again, similarly as higher personnel costs can be explained - by the
start-up operations that require an MFI to hire more IT designers and managers to build and manage this new technology, and perhaps more trainers to train staff. Hiring these additional staff members would lower the borrower per staff member ratio. Similarly to my analysis of operating and personnel costs, then, I would expect the true effects of mobile banking on borrower per staff ratio to only show up after the programs have been well instituted and after a fair share of clientele is using the technology.

I expect that when the mobile banking programs mature, the coefficient for mobile banking will become positive, as a staff member would be able to manage more borrowers if all the borrowers were using mobile banking to repay loans. Similarly, then my results for borrower per staff ratio may point to the need for MFIs to stick the course of implementing and encouraging use of the mobile banking technology.

*Mobile banking and portfolio at risk for 30 or more days*

I expected that mobile banking would be associated with lower rates of portfolio at risk, however my data shows no statistically significant relationship. Similarly to above results, I would accredit to these results to the newness of mobile banking programs, and would therefore prescribe the same policy recommendation – to continue support of this new technology, and for a researcher to return and reassess results in two years time.
**Policy implication I:**

**MFIs should encourage more widespread use of mobile banking technology**

MFIs should encourage more widespread use of the mobile banking technology within their clientele so that MFIs can reap the anecdotally reported cost-saving and efficiency-generating benefits of using mobile banking. Mobile banking makes MFIs more competitive by bringing a service of convenience to clients, and MFIs also gain through better ease of managing the loans. MFIs can encourage use of mobile banking through offering lower interest rates for people who pay and manage their loans by phone, and through marketing the technology and its use to current and potential clients.

**Mobile banking and average loan balances**

Mobile banking is associated with MFIs that have lower average loan balances. This indicates mobile banking is being used by MFIs that have clients who borrow smaller amounts, and are therefore generally poorer. This result is encouraging as it shows that the MFIs that serve poorer clients have not been shy in adopting mobile banking technology, and that poorer clients are being exposed to the technology. This shows that mobile banking can be a great option for banks that manage many loans that are smaller, or that seek to reach a poorer clientele.

Kenyan MFIs with mobile banking are associated with MFIs that have lower average loan balances. As discussed above, costs per loan portfolio are highest for MFIs when loan sizes are the smallest. Thus, the cost saving benefits of mobile banking are most needed in the higher cost per portfolio situations when there are many smaller loans -- in other words, when an MFI is serving the poorest clients. Mobile banking’s ability to bring efficiency to loan management

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would also be most realized when there are many loans being serviced by mobile systems. Both of these traits illustrate a natural relationship between mobile banking and the multitude of smaller loans sought by poorer clients. These theoretical links between mobile banking and poorer clients are observed in my results, as my results show that MFIs with mobile banking are associated with lower loan balances.

These quantitative results can be explained in either one of two ways. The first is that mobile banking helps MFIs serve people who borrow smaller amounts. Thus once an MFI institutes a mobile banking program, the MFI has the capacity to manage the many smaller loans of the lower market clients.

The second possible explanation for the negative relationship between mobile banking and average loan balances is that MFIs with already poorer clients are the ones adopting mobile banking. This relationship could be explained as MFIs with poorer target markets may see more value in adopting mobile banking as a way to help manage their clients, because they have so many smaller loans, and the costs of personally managing these loans is so high that these MFIs are better able to justify investing in a program that would make the management of these loans more affordable. As my regressions do not use panel data, it may be difficult to determine the direction of causation of this relationship.

In either case, results and theory illustrate that mobile banking and smaller loans go together. That mobile banking actually reaches poor people is also supported in CGAP’s investigation of demographics of mobile banking users in Mali, Pakistan, and India (Bold, 2011). Thus the policy recommendation is clear: mobile banking should be recognized as an important tool in outreach to poor clients, and thus should be promoted by MFIs as a tool to help streamline their loan management, and by policy makers at large as a tool that has special importance to
low-market MFI clients. Policy makers and MFI managers both have a role in supporting this important relationship between mobile and the potential for mobile banking to help with the management of loans, especially the smaller loans obtained by poorer clients that have a relatively high cost of management.

**Policy implication II: Mobile banking use should be encouraged in lower end clients**

*MFIs should prioritize mobile banking for low-income clients*

If an MFI has multiple defined markets it serves, and either is unable to bring mobile banking to its whole operations, or wants to institute a mobile banking pilot program, then the MFI would do well to phase in a mobile banking program to the poorest market it serves. It could do this by first offering mobile banking to only their poorest outreach division. Alternatively, if the MFI does not have a separate low-market division, it could target its marketing campaigns to the poorer neighborhoods it serves in order to influence the poorer clients to adopt mobile banking.

*Policy makers should support mobile banking friendly policies*

As mobile banking has special potential to help MFIs expand outreach in poorer markets, as a matter of policy to support opportunities for low-income people, policy makers should support a policy environment that is friendly towards mobile banking. It is beyond the scope of my paper to discuss intelligently the ways that policy makers can create environments that support mobile banking, but the CGAP and USAID offer many resources on this topic (Stephens, 2012 and Chemonics, 2010).
CONCLUSIONS

Results overview

An overview of this project’s results shows that mobile banking is a significant variable in many regressions tested, explaining variation in a number of MFI performance measures. The coefficients for mobile banking were different than expected for explaining variation in operating expenses, personnel expenses, and borrowers per staff. There was also no statistically significant relationship between mobile banking and portfolio at risk measures, when I had thought there would be. I attributed these theoretically surprising results to the newness of mobile banking programs, with the expectation that when the programs are more deeply adopted by the client base, that the benefits theoretically associated with mobile banking programs in MFIs would show up in the data.

The coefficient for mobile banking was negative as expected for average loan balance per borrower. This is an encouraging result for mobile banking programs in MFIs, because it means both that MFIs that serve lower end clients (as measured by average loan balance per borrower) are able to, and in fact are, implementing mobile banking programs. This result also shows mobile banking will be available to poorer clients. This result is encouraging because microfinance was designed to give financial access to the poorest, and because the smallest loans cost the most per dollar amount loaned to manage. Therefore the fact that mobile banking is associated with smaller average loan balances means that this is a tool that MFIs can use and in fact are using to reach out to poor people. This implies, also, that mobile banking may offer more marginal benefits to MFIs that offer smaller loans.
Relevance of results for the microfinance field outside of Kenya

This study uses data from MFIs located in Kenya, as Kenya has the deepest and most widespread use of mobile money in the developing world. Their MFIs have also the most experience implementing mobile banking programs. Using MFIs only from Kenya also has an added bonus of eliminating the national-based policy and operating environmental factors that could influence the results if MFIs from multiple countries were used. This means that the results from this study are illustrative of the Kenyan MFI field, and thus not necessarily externally valid.

However, this experiment is extremely relevant for MFIs in any developing country that might want to add mobile banking to their operations. Kenya’s experience in mobile money has been influential for those looking to implement mobile money programs in other countries (Dean, 2012), and the trends observed from their MFIs and mobile money experience should be studied as more countries and MFIs seek to integrate mobile banking services into microfinance.

Suggestions for future study

Many of my conclusions drawn from the results rest on the assumption that the mobile banking programs should be more widely used by an MFI’s clientele. Currently there is no measure available to quantify mobile banking penetration rates within each MFI. This investigation could be made better if MFIs started collecting information on how many people in the MFI are signed up, or are using mobile banking services to make loan payments and to receive loan payment reminders. The availability of this data would allow researchers to see if results differ based on the intensity of mobile banking usage.

Another improvement would come from using panel data, adding MFI-specific dummy variables, to control for all the time-constant characteristics of each MFI. At this time, I could
not add MFI-specific dummy variables, as this would eat away at the degrees of freedom in the model. My sample has 96 total observations, and my actual regressions have 57-72 observations after dropping observations. The 25 MFI-specific dummy variables would leave me with as little as 27 degrees of freedom in some of the regressions I performed, which are not nearly enough to give a statistically sound analysis. However, this dataset has the opportunity to grow by an estimated 25 observations per year, if all MFIs in the set stay in operation. This means that by including data from years 2011 and 2012, the dataset would then have around 150 observations, which might then be enough observations to perform regressions using MFI-specific dummy variables. Also, two years from now, I expect that mobile banking programs will become more prevalent for many of the MFIs, and the MFIs should be reaping the benefits, which would also bode well for finding my expected results. That being said, I plan to stay in touch with colleagues in Kenya and revisit this project in 2014.

One last idea for future research includes the use of instrumental variables in order to deal with the possible endogeneity problem. The endogeneity in my approach may arise because the MFI that is likely to adopt mobile banking is higher performing, has a larger client base, or already more efficiently run to begin with when compared to MFIs that did not adopt mobile banking. Key in isolating the direction of causation would be to find an instrument variable that would be highly correlated with mobile banking, yet uncorrelated with one of my five dependent variables. Devising and testing the model with instrumental variables can be a task for future researchers.
APPENDIX A: ATTACHMENTS

LIST 1:

Listing of 5 variables chosen to be dependent variables:
   1. Operating expense per loan portfolio
   2. Personnel expense per loan portfolio
   3. Borrowers per staff member
   4. Average loan balance per borrower
   5. Percentage of portfolio at risk for more than thirty days

These variables considered, and the reason they were not chosen to be dependent variables:
   6. Operating expense per assets – not chosen as it is similar to variable one, but with less significant results illustrated in the model
   7. Total expense per assets - not chosen as it is similar to variable one, but with less significant results illustrated in the model
   8. Financial expense per assets - not chosen as it is similar to variable one, but with less significant results illustrated in the model
   9. Average deposit balance – Would have been interesting to do analysis with respect to information about depositors as well, but there were only 50 observations left in the equations using this data, and results were not as strong. Also, depositors do not have to worry about repaying loans, so the potential impact of mobile banking on depositors is not as strong as it is for borrowing clients.
   10. Average deposit balance per depositor – same discussion as for variable number 9.
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