How Mobile Money Affects the Bottom Line: Evidence From Kenya

William Lawrence

Bachelor of International Economics

The University of British Columbia

Abstract

While there has been increasing interest in the economic effects of mobile money in Kenya, there is little empirical literature on the causal channels between mobile money usage and disaggregated household consumption. This paper leverages an instrumental variable strategy from Jack and Suri (2014) to identify the effects of mobile money on 12 household expenditure categories including health care, education, and food expenditure. The findings suggest that four categories - transportation, supporting family members, non-food durables, and total expenditure - change in an economically significant way with access to mobile money. This quantitatively reinforces several aspects of the surrounding literature while also raising new research questions related to the effects of mobile money on welfare.

Keywords: Mobile Money, M-PESA, Financial Inclusion, Kenya

1. Introduction

The mobile phone has been among the most rapidly adopted innovations in the world, with SIM cards and prepaid phone minutes now becoming ubiquitous in many developing economies. While there has been a large body of research pointing to the benefits of mass mobile phone adoption, this study will focus on "one of the most celebrated" (Suri 2017) results of mobile phones in developing countries: mobile money.

Mobile money is a broad term used for services that provide mobile phone owners the ability to deposit, transfer, and withdraw funds directly from their phone without owning a bank account. This category of services has reached widespread adoption with over 441 million registered accounts across the world and 222.6 million in Sub-Saharan Africa alone (GSMA 2015). The most successful and well-known mobile money product was launched in 2007 in Kenya by one of the country's main telecommunications companies, Safaricom. This product is called M-PESA and by 2016 has reached almost universal coverage in Kenya with approximately 96% of households having access to the service (Jack and Suri 2016).

While there are numerous papers about contextual benefits of mobile money and M-PESA, there remains to be a granular study of the channels by which mobile money effects individual disaggregated consumption. For this reason, this study will look to identify how M-PESA causes changes in 12 different household expenditure categories including medical expenses, education, and food expenditure. By having a stronger grasp on the individual consumption changes induced by this technology, the scholarly community can have a better understanding of the channels through which mobile money affects welfare.

To study how M-PESA has changed individual expenditure in Kenya, I analyzed data from a nationally representative survey that surveyed a random individual in 10,008 households across Kenya. To address potential endogeneity concerns around adoption of M-PESA, I will leverage an instrumental variable strategy that is largely informed by the work of Jack and Suri (2014). That is, I will use the percentage of a Kenyan county's population that is within a 1 KM range of a mobile money agent as an instrument for access to M-PESA. As I will demonstrate, agent location appears to be a valid instrument after considering the variable's relationship with M-PESA access, its lack of correlation with other endogenous variables, and its maintenance of an exclusion restriction.

The findings from this strategy show that M-PESA leads to economically significant consumption changes in transportation, supporting family members, non-durable goods, and total expenditure at the individual level. Specifically, the changes in these expenditure categories as a percentage of income are -81.4%, 51.1%, -11%, 140.8% respectively. These results, discussed in more detail in Section 6, in part validate earlier findings in the literature and introduce new topics of research around changes in individual welfare.

This paper is structured as follows. Section 2 will review the significant amount of literature around the topics of financial inclusion and the effects of mobile money. In Section 3, I will then introduce the 2016 FinAccess DataSet and explain the merits and novelties that reside in it. In Section 4, I will introduce my estimation strategy that aims to isolate the variation in

M-PESA access to infer causality with change in expenditure. Section 5 will then show the results from this estimation model and check the robustness of the model with different specifications. Lastly, Section 6 will discuss the conclusions drawn from the analysis and present possible channels of effects between access to M-PESA and individual welfare.

2. Literature Review

To best approach the literature, I will start at the overarching theme of financial inclusion and move the study downwards to the more relevant level of mobile money's effect on individual consumption.

2.1. Financial Inclusion

In recent years, there has been a mounting interest concerning financial inclusion in emerging economies. Financial inclusion, as defined in a World Bank report by Demirg-Kunt et al. (2012a), is "the development and maintenance of inclusive financial institutions which offer broad access to financial services, without price or non-price barriers to their use". In their report, the authors highlight the "sharp disparities in the use of financial services between high-income and developing economies and across individual characteristics". While this implies a negative picture, the global Financial Inclusion Index has generally indicated a positive trend over time as financial inclusion grows globally (Demirg-Kunt et al. 2012a). The story with African countries, for example, has been one of "positive developments in access to financial services in recent decades" (Demirg-Kunt et al. 2012b). The main reason for optimism, according to the authors, is a "bright spot in the expansion of financial services in the developing world" in the introduction of "mobile money" (Demirg-Kunt et al. 2012a) It is the aim of this literature review to understand the scope of the mobile money ecosystem, its economic effects on household consumption, and the empirical methods used to infer causality from its adoption.

2.2. Mobile Money

Mobile money is a relatively new tool that allows individuals to make financial transactions using cell phone technology (Jack and Suri 2011). This rapidly expanding tool has achieved the broadest adoption in East Africa, where in 2014, "20 percent of adults reported having a mobile money account" (Demirg-Kunt et. al 2014). This aggregate percentage is mostly driven by the mobile money situation in Kenya, where in 2016 the countrys dominant mobile money provider, M-PESA, is used by at least one individual in 96% of households (Jack and Suri 2016). M-PESA allows users to deposit money into an account stored on their cell phones, to send balances using SMS technology to others, including institutions or individuals, and to redeem deposits for regular money (Jack and Suri 2011). Mobile money as a whole has been a major force in banking the previously unbanked in emerging economies, increasing financial account registration in East Africa by 9% from 2011 to 2014 (Demirg-Kunt et. al 2014). The effects of these mobile money systems, including M-PESA, on household welfare have been well-documented by several scholars in the field, which is an encouraging indication of the value of this research for policy.

2.3. The Effects of Mobile Money on the Household

Fortunately, many researchers have empirically analyzed the effects of mobile money on households. Mbiti and Weil (2011) show that M-PESA use increases frequency of sending transfers, decreases the use of informal saving mechanismsand increases the probability of being banked. Morawczynski and Pickens (2009), in a similar vein, find that M-PESA “increases savings for both the banked and unbanked [and] improves womens empowerment”. While these are notable effects, they do not directly discuss the effects of mobile money on household level consumption. With this in mind, one outcome of mobile money worth exploring deeper is the ability for households to smooth consumption during negative economic shocks. The robustness of this claim has been reinforced to include various shocks, including sickness and death (Suri et al. 2014), an earthquake in Rwanda (Blumenstock et al. 2016), and even increased periods of violence in Kenya (Morawczynski 2009). In one prominent study focusing on Kenya, Jack and Suri (2014) argue that this ability to endure shocks is caused by the facilitation of risk sharing through a reduction in transaction costs. Risk sharing, according to the authors, is improved by M-PESA’s ability to reduce transaction costs and therefore facilitate remittances to households in a family network during periods of negative shocks. After reviewing this study and all the aforementioned literature, Suri (2017) maintains that facilitated remittances is the most “salient” causal channel between mobile money and household welfare.

This argument proves to be quite relevant when looking at other contexts where remittances were not a large part of the equation. In Afghanistan, Blumenstock et al. (2015) conducted a randomized control trial (RCT) whereby some employees receive their wages through a mobile money service and others receive cash payments. In this context, employees were found to be no more likely "to send or receive transfers than individuals receiving cash-based payments" while also reporting "very few differences in self-reported outcomes" (Blumenstock et al. 2015). To corroborate Suris emphasis on remittances with a different example, Aker et al. (2014) conducted an RCT in Niger to distribute unconditional cash payments in response to the 2009-2010 food crisis where the comparison was made between households that received transfers in cash or through mobile money. These authors found that households receiving "mobile money transfers had better nutrition, with a 10-16% more diversified diet" (Aker et al 2014). We can thus draw two preliminary hypotheses from the literature mentioned so far: that remittances appear to be a major causal channel between mobile money and household level effects and that mobile money appears to have causal effects outside of the Kenyan context.

From the hypotheses above, a final broad question still remains unexplored: what are the effects of mobile money on disaggregated household consumption? One prominent answer comes from a randomized control trial in Kenya which showed a strong consumption response at the aggregate and disaggregate level to an unconditional cash transfer program through M-PESA (Haushofert and Shapiro 2012). Specifically, they found that food expenditures increased close to proportionally to overall non-durable expenditure, health and education expenditure increased more than proportionally, and alcohol and tobacco expenditures did not increase. Although they argue the point, they do not make an empirical case that distinguishes the effect of the cash transfer itself from the effects of receiving money through M-PESA. This gap is later filled by Munyegera and Masumoto (2016) who succeed in isolating variation of mobile money from a two-year panel from 2009 and 2012 in Uganda, finding that households who use mobile money "experience a significant increase in per capita consumption, both in aggregate form and disaggregated components". These two studies are highly relevant to my area of interest and provide positive signs that there may be an effect of mobile money on household welfare, but what remains to be proved is the robustness of these findings when applied to Kenya and more recent data.

2.4. Previous Empirical Strategies

A key challenge in this study will be isolating the effects of M-PESA through a source of exogenous variation. To inform my strategy, I will look at the empirical strategies that currently exist in analyzing causal inference with mobile money. Mbiti and Weil (2011) present an instrumental variable (IV) strategy to isolate variation for M-PESA usage where they use responses to select questions from a Kenyan Financial Inclusion survey as the instrument for M-PESA adoption. The instruments, including trust level of friends, reliability of the post office and the perceived price of money transfers in 2006, seem plausible but I am concerned that responses to these survey questions are not randomly distributed. One potential violation of the randomness, for example, may be that households closer to the post-office who deem it more reliable and were also located in urban areas with higher access to technology.

Other researchers have used natural experiments to understand the variation in access and use mobile money. In Rwanda, Blumenstock et al. (2016) used responses to an earthquake to understand the actions taken with mobile money in the wake of a natural disaster. A similar study took place in Tanzania, where Economides and Jeziorski (2015), exploit a natural experiment in an unanticipated increase in transaction fees to understand the patterns of peer-to-peer transaction volume of mobile money. Both of these identification strategies are indeed compelling, but I am mostly concerned with understanding household consumption during the baseline period when shocks are not occurring.

With this concern in mind, I will turn to the very strong IV strategy introduced by Jack and Suri's (2014) work on the effects of mobile money on risk sharing. To identify the causal effects of M-PESA on the economic well-being of households, they used geographic proximity of households to M-PESA agents to identify exogenous variation in access to M-PESA. They show in their work that geographic rollout of agents was not systematically correlated with the initial level of, or changes in, individual and household characteristics that might have been associated with future outcomes (Suri and Jack 2016). Since they use the Kenyan context in their own study, I believe that this identification strategy will be the most appropriate when studying disaggregate expenditure at the household level. I will, however, check the validity of the instrument by discussing potential violations to the exclusion restriction and adding several robustness checks at the end.

3. Data

In order to understand how M-PESA affects disaggregated consumption, I will use two data sets from a national household survey collected jointly by the Central Bank of Kenya, Financial Services Deepening (FSD) Kenya, and the Kenya National Bureau of Statistics. The first dataset is the 2016 FinAccess Household Survey (Central Bank of Kenya, FSD Kenya, Kenya National Bureau of Statistics 2016), which measures access to and demand for financial services among adults in a nationally representative survey. The target sample was 10,008 households from across Kenya where one respondent per household, age 16 or older, was randomly selected to answer the questionnaire. This dataset contains the majority of the variables required for my study. This includes whether survey respondent's have an M-PESA account, the treatment of interest, as well as the different expenditure categories as percentages of income of the surveyed individual, the outcomes of interest. To be explicit, I will study the effect of M-PESA on the following 12 categories: food, non-food items, non-food durables, mobile airtime, transportation, education, household bills, medical bills, paying off debts and loans, rent/mortgage, savings/investments, supporting family members and total expenditure.

The second dataset is a subset of the 2016 FinAccess National Survey that includes details on the approximately 66,000 mobile money agents across Kenya. (Bill and Melinda Gates Foundation, Central Bank of Kenya, FSD Kenya 2016). These details include services offered, exact location of operations, and when they became certified as an agent. The main purpose of this dataset is to calculate the agent density for a given county. I will define agent density as the percentage of the population within range of at least one mobile money agent. The distribution of agent density can be seen in Figure 2 (detailed breakdown in Appendix B).

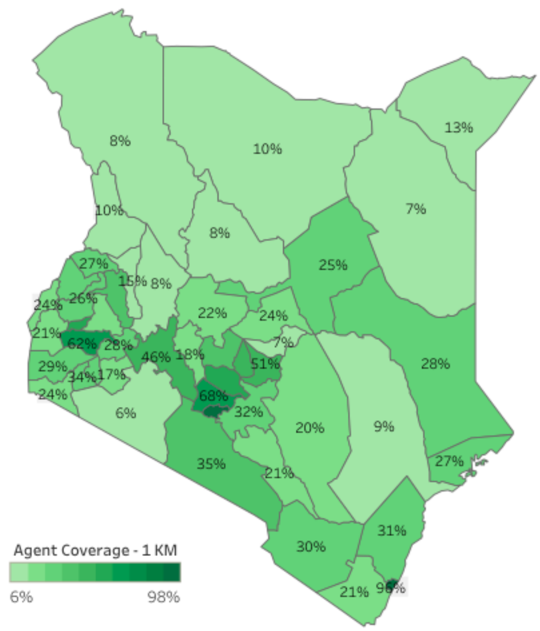

Figure 1: Percentage of county within 1 KM of a mobile money agent.

Both of these datasets reflect the time period between August 18, 2015 - October 15, 2015 and this survey has been conducted for three other years in the past (2006, 2009, and 2013). The geographic scope of the survey, as well as my study, will be all of Kenya clustered at the Enumeration Area (EA) level, which contains 833 clusters.

3.1. Sample Size

One important distinction to reiterate is that this study will be using individuals as the unit of observation when analyzing the effects of M-PESA, rather than the household. This is important in explaining why some expenditures may exceed 100% of income for that individual. These types of results were often found when the participant in the household (who was randomly selected during the process) was not the primary breadwinner in the household but still conducted a large amount of purchases for the household. To ensure that my results are truly representative of Kenya, I have selected a relevant sample size of individuals to study. To do this, I removed a series of outliers, merged districts that are within the same county and joined the dataset that contains the instrument variable. Details of these transformations can be found in Appendix A.

Table 1: Summary Statistics

Variables	**Mean**	**SD**
M-PESA User (%)	0.65	0.48
Own Cell Phone (%)	0.73	0.44
Log Total Income Per Month (KShs)	8.60	1.27
Education of Respondent	2.25	0.84
Female Respondent (%)	0.62	0.49
Age of Respondent	37.11	16.65
Household Size	4.38	2.48
Number of Children in Household	2.24	2.01
Urban Household (%)	0.42	0.49
Female Household Head	0.27	0.45
Expenses as Percentage of Income (KShs)		
Food	1.25	3.39
Non-Food Items (ex. Soap)	0.29	0.80
Non-food Durable (ex. Furniture)	0.01	0.16
Mobile Airtime Expenses	0.15	0.55
Transportation	0.21	0.64
Education	0.65	2.47
Household Bills	0.07	0.43
Medical and Health Care	0.17	0.89
Paying off Debts and Loans	0.13	0.50
Rent/Mortgage	0.09	0.43
Savings/investment	0.20	0.75
Supporting Family Members	0.12	0.64
Total Expenditures	3.34	6.97
County Population Within Range of Mobile Money Agent		
Population Within 1 km (%)	0.34	0.25
Observations		7756

The final sample size for this study was 7,756 individuals with a slew of differences that reflect the diversity of Kenya. This diversity can be seen in Table 1. It is also important to note that only 65% of the sample reports having an M-PESA account. This will be important for understanding the difference between the treatment group of M-PESA users and the control group in this natural experiment.

4. Empirical Strategy

4.1. Base Specification

At the simplest form, the relationship between access to M-PESA and disaggregated expenditure categories can be written as:

$$EXPENSE_i = \alpha + \delta_1 MPESA + \epsilon_i \tag{1}$$

where $EXPENSE_i$ rotates through the 12 expenditure categories for individual i, MPESA is a dummy variable that represents if the individual i has an M-PESA account and δ_1 is the treatment effect of M-PESA access. However, it is clear that this model suffers from endogeneity problems. For example, it is very likely that people in urban environments would have higher adoption rates of M-PESA because they have greater access to mobile money service providers. This example, and likely other endogeneity concerns, would bias the estimates for δ_1. The literature shares these same concerns and the instrumental variables used for this paper comes from peer reviewed papers in this field. I will thus use the percentage of the county that is within 1 kilometer of a mobile money agent as an instrument for access to M-PESA. This instrument, in conjunction with some additional controls, should effectively address the problem of endogeneity and instill confidence in my findings.

4.2. Controls and Standard Errors

Before presenting my 2SLS estimation equations, I would like to address the blaring concern that many other variables will affect both the treatment, M-PESA access, and outcomes, household spending habits, in the model. Therefore, my model will contain three control vectors, one for individual level controls, I_i, another for household controls, H_h, and a third for financial controls, F_i. The household vector will include a dummy for urban households, female household head, and number of school aged children in the household. The vector for individual controls will include mobile phone ownership, monthly income, age, education, and a dummy for female. Lastly, the financial controls will be a dummy for 12 different income sources (including categories like farming and part-time employment) and another dummy for having a savings account with a Kenyan bank. Adding these controls will remove many of the likely channels of effect that could bias my coefficient of interest.

To additionally control for unobservables in the model, I will cluster my standard errors at Enumeration Area (EA) level of observation. These EAs represent the smallest level of geographic cluster available in the data. Clustered errors allow for the highly likely possibility that observations in the dataset are correlated. That is, individuals in the same enumeration area are likely to share some traits such as education level, spending on transportation, or income sources. By clustering standard errors in my 2SLS estimations, I hope to increase the precision of my estimates and make the model more faithful to reality.

4.3. Two-Stage Least Squares Specification

With controls and clustered standard errors in mind, my first stage equation is:

$$MPESA_{ihc} = \alpha + \gamma_1 AgentCoverage_c + I_i + H_h + F_i + \epsilon_{ihc} \tag{2}$$

where $AgentCoverage_c$ is the percentage of the county population that is within 1 kilometer of a mobile money agent. The other variables vary across three dimensions: individuals i, household h and county c This first stage will demonstrate the relevance of the instrument in predicting the treatment with several important controls in place. From the first stage, we obtain fitted values for access to M-PESA, $\widehat{MPESA}_{ihc}$, to get to the following second stage equation:

$$EXPENSE_{ihc} = \alpha + \beta_1 \widehat{MPESA}_{ihc} + I_i + H_h + F_i + \epsilon_{ihc} \tag{3}$$

My coefficient of interest in this equation is β_1 as this will tell me how access to M-PESA affects spending on the 12 expense categories listed above. My initial hypothesis is that most expenditure categories will not have significant values for β_1 as access to M-PESA would not change, for example, how much food your family will need in a given month. There are two main effects I hypothesize will be evident from the data. The first is that discretionary spending will increase as M-PESA reduces economic transaction costs and thus facilitates the purchase of new, non-essential goods. This effect would be reflected as a positive coefficient on the Total Expenditures as Percentage of Income category. Another effect that I anticipate is that the category for Supporting Family Members will increase. This is reflected in the literature that shows mobile money facilitates the remittances process and also allows for money to be sent in response to economic shock (Jack and Suri 2014).

5. Results

5.1. OLS Specification

It will be important to have a baseline specification for which to compare the results from my 2SLS model. For this reason, I will begin by displaying the results from a model that adds the individual, household, and financial control vectors to the model in (1). This will be:

$$EXPENSE_{ihc} = \alpha + \theta_1 MPESA_{ihc} + I_i + H_h + F_i + \epsilon_{ihc} \tag{4}$$

The results for this model can be found in Table 2A and Table 2B. As can be seen, they suggests that access to M-PESA increases the share of an individual's budget dedicated to rent expenditure while decreasing the percentage of income dedicated to medical expenses. The concern with these findings, however, is that the treatment is non-randomly distributed and the decision to adopt M-PESA is likely to be influenced by other unobservable factors. For example, while θ_1 in the regression with medical expenditure as the dependent variable is significantly negative, one could argue that people who choose to adopt M-PESA have better health overall because of other unobservable factors. For this reason, I cannot interpret these findings as causal and will instead develop an instrumental variable framework that uses the population of a county within 1 km of at least one mobile money agent to isolate the variation in M-PESA access.

Table 2A: OLS Regression						
	Dependent Variable: Expenditure Catgeories As Percentage of Income					
Independent Variable	Food	Non-Food	Non-Food Durable	Mobile Airtime	Transport	Education
M-PESA	-0.033	0.069***	-0.006	0.031	-0.005	-0.022
	[0.117]	[0.025]	[0.006]	[0.197]	[0.084]	[0.333]
Controls						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All standard errors are clustered at the enumeration area level (833 clusters).

Table 2B: OLS Regression						
	Dependent Variable: Expenditure Catgeories As Percentage of Income					
Independent Variable	Utilities	Medical	Rent	Total Expenditure	Savings	Supporting Family
M-PESA	-0.004	-0.091***	0.054***	0.022	-0.001	0.018
	[0.050]	[0.095]	[0.018]	[0.017]	[0.067]	[0.052]
Controls						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All standard errors are clustered at the enumeration area level (833 clusters).

5.2. First Stage

My first stage regression will test specifications of the model described in (2). The results for this model, outlined in Table 3, demonstrates that agent coverage has a significantly positive relationship with M-PESA even after controlling for important variables like mobile phone ownership, income, age and having a savings account. It is important to note that some variables such as urban, number of school aged children, and female household head are insignificant in this regression but remain important to control for in the main regression. For example, school aged children is a necessary control when examining the effect of M-PESA access on education spending as households with students will obviously dedicate a higher share of their income to this expense.

Table 3: First Stage Regressions

	Dependent Variable: M-PESA Account Ownership				
	No Controls	Individual Controls	Household Controls	Financial Controls	All Controls
Agent Coverage - 1 KM	0.424***	0.128***	0.342***	0.229***	0.093***
	[0.509]	[0.128]	[0.029]	[0.021]	[0.018]
Has a Mobile Phone		0.640***			0.581***
		[0.011]			[0.013]
Ln Monthly Income		0.044***			0.027***
		[0.003]			[0.003]
Female		0.001			0.001
		[0.008]			[0.008]
Age		0.002***			0.001***
		[0.0002]			[0.0002]
Education		0.086***			0.062***
		[0.033]			[0.060]
Female Household Head			-0.064***		-0.012
			[0.012]		[0.010]
Urban Dummy			0.121***		0.002
			[0.015]		[0.009]
# School-Aged Children			0.001		0.001
			[0.003]		[0.001]
Has a Savings Account				0.415***	0.184***
				[0.012]	[0.011]
Income Source Dummy	No	No	No	Yes	Yes
F-Stat	240.21	2366.35	83.240	306.090	979.770
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered
Observations	7756	7756	7756	7756	7756

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, "Agent Coverage - 1KM" refers to the population of a county within 1 KM of at least one mobile money agent. All regressions clustered at enumeration area level (833

5.3. Reduced Form

Next, I will see if the instrument has any relationship with the 12 expenditure categories that are being studied. This can be found by running the specification in (3). The findings in Table 4A and 4B show that agent coverage only has a significant relationship with four of the expenditure categories: non-food durables, transportation, total expenditure and supporting family members. While the reduced form does not speak directly to M-PESA access, it does foreshadow which expenditures M-PESA access may alter.

Table 4A: Reduced Form

	Dependent Variable: Expenditure Catgeories As Percentage of Income					
Instrument Variable	Food	Non-Food	Non-Food Durable	Mobile Airtime	Transport	Education
Agent Coverage - 1 KM	-0.902	-0.015	-0.011**	-0.010	-0.080***	-0.031
	[0.187]	[0.036]	[0.006]	[0.027]	[0.026]	[0.098]
Controls						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. "Agent Coverage - 1KM" refers to the population of a county within 1 KM of at least one mobile money agent. All regressions clustered at enumeration area level (833 clusters).

Table 4B: Reduced Form

	Dependent Variable: Expenditure Catgeories As Percentage of Income					
Instrument Variable	Utilities	Medical	Rent	Total Expenditure	Savings	Supporting Family
Agent Coverage - 1 KM	0.033	-0.051	-0.037	0.138***	0.052	0.050**
	[0.029]	[0.039]	[0.034]	[0.032]	[0.005]	[0.024]
Controls						
Individual	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Household	Yes	Yes	Yes	Yes	Yes	Yes
Standard Errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered

Notes: * p < 0.10, ** p < 0.05, *** p < 0.01. "Agent Coverage - 1KM" refers to the population of a county within 1 KM of at least one mobile money agent. All regressions clustered at enumeration area level (833 clusters).

Another point to note is that with the control vectors, I am assuming that I have controlled for all possible violations of the exclusion restriction. That is, I have included controls to remove possible channels of effect between the instrument and all expenditure categories. Jack and Suri (2014) make the same assumption after investigating whether the agent rollout was associated with observables in their data. After checking correlations between agent rollout and household wealth, cell phone ownership, measure of education and household access to various financial services, they "find little evidence that the agent rollout is correlated with most household-level observables" (Jack and Suri 2014). Based on the strength of my controls as well as the existing scholarly corroboration, I will continue with the assumption that the exclusion restriction is not violated in this specification.

5.4. Main Effects

Table 5: Second Stage Regressions

		2SLS (Instrument: Agent Coverage - 1 KM) Independent Variable: M-PESA		
Dependent Variable	OLS	Robust SE	Clustered SE - County Level	Clustered SE - Enumeration Area
Food	-0.033	-0.924	-0.924	-0.924
	[0.114]	[1.540]	[2.501]	[1.632]
Non-Food	0.069***	-0.149	-0.149	-0.149
	[0.026]	[0.324]	[0.748]	[0.369]
Non-Food Durable	-0.006	-0.110*	-0.110	-0.110*
	[0.005]	[0.060]	[0.100]	[0.063]
Mobile Airtime	0.031	-0.102	-0.102	-0.102
	[0.022]	[0.270]	[0.301]	[0.270]
Transport	-0.005	-0.814***	-0.814**	-0.814***
	[0.025]	[0.283]	[0.337]	[0.296]
Education	-0.022	-0.315	-0.315	-0.315
	[0.107]	[0.949]	[1.264]	[1.002]
Utilities	-0.004	0.342	0.342	0.342
	[0.015]	[0.291]	[0.487]	[0.299]
Medical	-0.091**	-0.527	-0.527	-0.527
	[0.043]	[0.390]	[0.047]	[0.394]
Rent	0.054***	-0.382	-0.382	-0.382
	[0.017]	[0.234]	[0.485]	[0.258]
Total Expenditure	0.022	1.408***	1.408***	1.408***
	[0.013]	[0.362]	[0.527]	[0.401]
Savings	-0.001	0.528	0.528	0.528
	[0.030]	[0.494]	[0.468]	[0.507]
Supporting Family	0.018	0.511**	0.511	0.511**
	[0.037]	[0.257]	[0.367]	[0.265]

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, "Agent Coverage - 1KM" refers to the population of a county within 1 KM of at least one mobile money agent. Individual, household, and financial controls included in each regression. All regressions clustered at enumeration area level (833 clusters).

To complete my preliminary estimation strategy, I will now present my findings from the two-stage least squares regression using the agent coverage instrument. These results, which are presented in Table 5, are both remarkably different from the OLS results and remarkably similar to the reduced form estimates. There are four specifications where β_1, the coefficient on access to M-PESA, represents a significant change in expenditure. These are in the cases of change in expenditure on non-food durables, transportation, total expenditure and supporting family members. Before discussing the economic significance as well as the channels between M-PESA access and expenditure, it is worthwhile discussing the robustness of these findings under different specifications.

5.5. Robustness Checks

While these results are grounded in the literature, it is worth addressing potential problems in the model. The most obvious group of criticism could rise from the plausibility that M-PESA could reflect characteristics that are unobservable but related to spending habits, for example a higher propensity to consume on the margin. This would necessarily leave bias in the estimation of β_1 in the main result estimation. To address this concern, I run two robustness checks that replace the treatment, which is currently measured by M-PESA account ownership, with both frequency of M-PESA use and estimated travel time to closest M-PESA agent.

The first robustness check uses frequency of M-PESA use as the treatment in order to capture the effect of using the service rather than idly owning an account. As can be seen in column 2 of Table 6, the results with this specification are very similar to my preferred specification. The main difference is that β_1 in this specification with the dependent variable supporting family falls with the new treatment, although it is still statistically significant at the 10% level. This is intuitively appealing as expenditure towards supporting family likely occurs in larger, less frequent sums of payment rather than small amounts daily. In other words, variance in expenditure towards supporting the family is not explained as much by frequency of transactions as it would be from having access to the service.

Table 6: Robustness Checks: Treatment Variables

	2SLS (Instrument: Agent Coverage - 1 KM)		
Dependent Variable	Has M-PESA account	M-PESA Use Frequency	Estimated Travel Time to closest M-PESA agent
Food	-0.924	-0.319	0.0032
	[1.540]	[0.570]	[0.0057]
Non-Food	-0.149	-0.051	[0.0097]
	[0.324]	[0.127]	[0.0013]
Non-Food Durable	-0.110*	-0.038	0.0004*
	[0.060]	[0.024]	[0.0002]
Mobile Airtime	-0.102	-0.035	0.0004
	[0.270]	[0.095]	[0.0010]
Transport	-0.814***	-0.281**	0.0029***
	[0.283]	[0.123]	[0.0097]
Education	-0.315	-0.109	0.0004
	[0.949]	[0.347]	[0.0036]
Utilities	0.342	0.118	-0.0013
	[0.291]	[0.108]	[0.0011]
Medical	-0.527	-0.182	0.0021
	[0.390]	[0.143]	[0.0014]
Rent	-0.382	-0.132	0.0013
	[0.234]	[0.094]	[0.0009]
Total Expenditure	1.408***	0.487***	-0.0046***
	[0.362]	[0.168]	[0.0013]
Savings	0.528	0.182	0.0018
	[0.494]	[0.178]	[0.0019]
Supporting Family	0.511**	0.177*	-0.0018*
	[0.257]	[0.100]	[0.052]

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, "Agent Coverage - 1KM" refers to the population of a county within 1 KM of at least one mobile money agent. Individual, household, and financial controls included in each regression. All regressions clustered at enumeration area level (833 clusters)

The second specification changes the treatment to estimated travel time to closest M-PESA agent. This specification similarly shows statistical significance in the same expenditure categories as the base specification. It is worth noting that although the signs of the treatment coefficients are the opposite of the base specification, they are implying the same effect because greater distance from an M-PESA agent implies less access to the service.

6. Conclusion

While some findings so far have been statistically significant, what remains to be discussed is the economic significance of these effects. In other words, it is now time to discuss if and how M-PESA affects welfare for Kenyans. After interpreting the results from the model, it can be said that after all other variables are held constant, access to M-PESA leads to economically significant consumption changes in transportation, supporting family members, non-durable goods, and total expenditure at the individual level. Explicitly, the changes in these expenditure categories as a percentage of income are -81.4%, 51.1%, -11%, 140.8% respectively. Below, I will analyze and speculate as to the channels that lead M-PESA to have such major changes to individual welfare.

To begin, mobile money's effect on transportation is very well supported by existing literature. In her 2017 literature review on mobile money, Suri (2017) concludes that one of mobile money's two main use cases is for "geographically disparate transactions" (Suri 2017). This logic is intuitively appealing as long-distance transaction have the largest economic costs associated with them and can be easily substituted by a mobile money transaction. Thus, M-PESA's ability to reduce these transaction costs also decrease the financial costs associated with transportation in the forms of bus fares or gas payments. Suri (2011) illustrates this case further by noting that "the average transaction [using M-PESA] traveled 200 km in 2008, which would be an approximately $5 bus ride" whereas using M-PESA "instead, consumers paid a $0.35 fee (given the average transaction size)". This example largely illustrates the reduction in transportation costs caused by M-PESA.

In a similar vein, the expenditure to supporting family likely sees an increase due to M-PESA's ability to facilitate remittances, the next significant change in expenditure. As noted in Section 2, remittances have been identified as an important channel between mobile money services and welfare. Using natural experiments from shocks including sickness and death (Suri et al. 2014), an earthquake in Rwanda (Blumenstock et al. 2016), and even increased periods of violence in Kenya (Morawczynski 2009), facilitated remittances through mobile money have demonstrated the ability to help smooth consumption, share risk, and expand financial support networks over large geographical ranges. Thus, the main channel between M-PESA and increased spending to supporting families is likely driven by the lower economic costs associated with maintaining financial support networks.

One finding that warrants further study is the 11% decrease in spending on non-food durables. In conjunction with the 140.8% increase in total expenditure, it may be possible that consumption shifts from larger, non-durable purchases to smaller non-necessity goods. This, however, is simply a conjecture and this finding requires more scholarly research to validate the channels between mobile money and decreased non-food durable expenditure.

Finally, total expenditure appears to increase sharply with access to M-PESA. This claim is largely supported by the various studies in Kenya (Jack and Suri 2017), other parts of Sub-Saharan Africa (Munyegera and Matsumoto 2016), and indeed many economies where mobile money is introduced (Batista and Vicente 2013). In their study, Munyegera and Matsumoto (2016) present a competing result regarding aggregate consumption changes, claiming that mobile money access is associated with a 69% increase in household per capita consumption in Uganda. The difference in context as well as using a household per capita measure rather than individual consumption measure could explain the disparity in the results. Jack and Suri present a series of possible reasons for the increased aggregate consumption in the Kenyan context, including facilitated "transfers between individuals with different propensities to consume", "allowing greater access to credit, both formally...and informally", and "smoothing consumption through informal risk sharing" (Jack and Suri 2016). These channels are challenging to evaluate individually but it is reassuring that the 140.8% increase in individual consumption is well-supported by the literature.

After reviewing the results, two things become abundantly clear. First, there appears to be an economically significant change in individual consumption induced by access to M-PESA. Second, these findings warrant further research into understanding the mechanisms through which mobile money access affects disaggregated consumption. In terms of further research, academics could benefit from understanding the type of consumption substitutions that occur when mobile money is adopted. As demonstrated in the bus fare example from Suri (2011), there exists many new opportunities for governments and private enterprise alike to capitalize on the new services being demanded in an economy with ubiquitous access to mobile money.

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Appendix A. Applied Transformations

Several transformations were necessary to ensure this dataset was ready for analysis. The first was the creation of dummy variables for female respondents, female household heads, and mobile phone owners from previously categorical variables.

Another set of necessary transformations was consolidating the treatment variable into a dummy. Because I am interested in the effects of M-PESA, I dropped users that had either another mobile money service or M-PESA and another service. This resulted in dropping 52 observations (less than 1% of the total observations). In order to create a dummy variable for M-PESA users, I also needed to merge the results of a question that asked if respondents have an M-PESA account. The three options for respondents were Currently have, Used to have or Never had M-PESA. I merged the responses from Used to have (252 observations) and Never had (2,698 observations) to create a dummy variable for current M-PESA user, which can be found at the top of Table 1.

Due to the protection of identities in the 2016 FinAccess survey, it was not possible to calculate agent density based on a perimeter around the household itself as in other studies (Jack and Suri 2016). Thus, I instead calculated the percentage of the county that was within 1 KM of a mobile money agent.

Before merging the datasets, I needed to ensure that the same county names were used in each dataset. While most were the same, several counties from the FSD mobile money agent mapping did not have a direct equivalence in the FinAccess dataset. Thus, the following changes were made:

1. Meru Center, Meru North, and Meru South were merged into one county Meru in accordance with the FinAccess dataset. The agent coverage was calculated as an average across the three regions individual coverage.
2. Nandi North and Nandi South were merged into one county Nandi in accordance with the FinAccess dataset. The agent coverage was calculated as an average across both regions individual coverage.
3. Marekwet and Elgeyo Marekwet were merged into one county Elgeyo Marekwet in accordance with the FinAccess dataset. The agent coverage was calculated as an average across both regions individual coverage.

Appendix B. Distribution of Agent Coverage

Appendix B: Percentage of County Within 1 KM of Mobile Money Agent

Coverage Level	Population (%)	Counties	Observations
Less than 10%	14.66	8	1,137
10% - 20%	14.16	6	1,098
20% - 30%	28.71	15	2,227
30% - 40%	17.65	8	1,369
40% - 50%	4.29	3	333
50% - 60%	6.77	3	525
60% - 70%	4.74	2	368
70% - 80%	-	-	-
80% - 90%	-	-	-
More than 90%	9.01	2	699
Mean	12.5	5.88	969.5
SD	7.66	4.17	594.05
Observations		47	7,756