Interoperability Between Mobile Money Providers in Tanzania

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Abstract

This paper examines the impact of interoperability between mobile money providers (MMPs) on mobile money adoption in Tanzania. The introduction of account-to-account (A2A) interoperability, which allows users to transfer funds between accounts across different MMPs, was expected to foster broader adoption by leveraging network externalities and reducing transaction costs. Using data from the Tanzania National Panel Survey (NPS), I develop a differentiated product demand model to estimate the effect of interoperability on mobile money adoption. The model captures how household preferences for interoperability vary by key characteristics such as wealth, education, and urban residence. Results show that households, on average, place a positive value on interoperability, with wealthier, more educated, and urban households exhibiting a stronger preference for interoperable services. This study contributes to the literature on financial inclusion and the importance of rgulatory framework in driving mobile money adoption.

1 Introduction

Mobile money is a new financial technology in developing countries that allows people to save, receive, and store money using a mobile phone. The service is usually provided by mobile network operators (MNOs) and differs from mobile banking in the sense that mobile money accounts do not need to be linked to an account at a formal financial institution (bank).[1] The only prerequisite for opening a mobile money account is the ownership of a SIM card. Given the high rate of mobile phone penetration in developing countries, mobile money is a widely accessible tool that can help promote financial inclusion.

Financial exclusion remains a major issue in many developing countries. Demirguc-Kunt et al. (2017) report that about 1.7 billion adults worldwide remain unbanked. In Tanzania, 46.6% of adults did not have an account at a financial institution (bank, mobile money provider, or another

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[1]This is at the individual level, mobile money providers in some countries are still required to form a partnership with a formal financial institution (for example, in Uganda).

financial institution) in 2017.[2] Including the world's poorest in the financial system can enable their investments in health, education, and businesses, which can be crucial in helping them escape poverty. In general, financial inclusion can improve well-being, particularly that of marginalized populations, and drive economic development (Karlan et al., 2016; Demirguc-Kunt, Klapper and Singer, 2017). Since mobile money can help achieve greater financial inclusion it is crucial to find ways to increase its adoption.

Numerous studies have shown positive impacts of mobile money on several outcomes. Mobile money allows households to increase their consumption (Suri and Jack, 2016; Munyegera and Matsumoto, 2016), improve their food security (Murendo and Wollni, 2016), and increase their savings (Suri and Jack, 2016; Munyegera and Matsumoto, 2015; Mbiti and Weil, 2016; Batista and Vicente, 2020; Demombynes and Thegeya, 2012). Mobile money is also an instrument that allows households to better cope with financial risk through receipt of remittances from relatives living in other geographic areas (Jack and Suri, 2014; Riley, 2018; Blumenstock, Eagle and Fafchamps, 2016).

Previous studies, both within-country and cross-country, attempted to shed light on what drives mobile money adoption. Munyegera and Matsumoto (2016) find that significant determinants of adoption by households in Uganda are ownership of a mobile phone, having a migrant worker in the household, distance to the nearest mobile money agent, and the value of total assets. They do not find a gender or an age effect. Similarly, Weil, Mbiti and Mwega (2012) find no gender effect in the context of Kenya, Tanzania, and Uganda. However, they do find that mobile money adopters tend to be younger, wealthier, and are more likely to live in urban areas. Gutierrez and Singh (2013) use the Global Findex data to understand what regulatory frameworks are most conducive to the success of mobile banking in a cross-country analysis. They particularly find that a regulatory framework that promotes interoperability leads to higher mobile money adoption among the poorest.

To understand adoption of mobile money, it is important to recognize that it is a network good. The utility that a consumer derives from using such good depends on the total number of agents consuming that good.[3] In other words, the utility is a function of the size of the network. A larger

[2]According to the World Bank's Global Findex data. Accessed at `https://globalfindex.worldbank.org/index.php/#data_sec_focus`.

[3]Notable examples of network goods are telecommunication technologies (telephones, social networks), payment

network of users of a given good allows consumers to achieve greater utility and increases their probability of adoption. Network externalities change the nature of competition between firms as well as the characteristics of the market equilibrium. Consumers often fail to internalize the benefits stemming from adoption of a network good, and therefore, the adoption of network goods is likely to be suboptimal in an unregulated environment. From the point of view of maximizing the total welfare, unregulated markets may fail to give consumers proper incentives to maximize their overall surplus (Farrell and Saloner, 1985; Katz and Shapiro, 1985).

Market structure matters for the extent of network effects. Rohlfs (1974) studies the market where network goods are supplied by a monopoly. He finds that network externalities can generate sizeable demand-side economies of scale and that multiple equilibria, in terms of the total number of users, are possible at a given price. An equilibrium with a small number of users can be welfare-maximizing since the benefits of a small network do not surpass the cost of adoption for most consumers. On the other hand, an equilibrium with a large number of users can also be sustained since the larger user base leads to a higher utility from adoption that can exceed the costs. In the context of mobile money in developing countries, an equilibrium with a larger user base is more desirable due to the positive impacts of mobile money on financial inclusion and other outcomes (as discussed earlier).

Nowadays, in most countries, mobile money services are not provided by a monopoly but rather by two or more companies. In a setting with multiple firms, the demand-side economies of scale might be less important if the goods supplied by different firms are incompatible. Incompatibility implies that users on one network derive zero utility from the number of users on a competing network. The question of achieving compatibility in the provision of network goods then becomes crucial. Matutes and Regibeau (1988) and Economides (1989) find that there can be incentives for producers to make their products compatible in the absence of network externalities. In the context of network goods, smaller firms (as opposed to larger firms) might be in favor of greater compatibility (Katz and Shapiro, 1985). However, there is also room for public policy. Governments have the power to require product compatibility. For example, such regulation was enforced in the mobile telecommunications industry in Europe. The European Parliament required mobile phones to comply with the same technical standards in all countries under its jurisdiction, which allowed

systems (credit cards, digital wallets), and digital platforms (office software, videoconferencing software).

mobile phone users to be able to use their devices in other European countries (Pepall, Richards and Norman, 2008, p. 654).

In the present context, interoperability between mobile money providers (MMPs) has been discussed in the policy sphere as a tool to increase adoption of mobile money via stronger network effects and reduced transaction costs. Note that there are two types of interoperability. The first type allows transactions to move seamlessly between mobile money accounts and the formal bank sector. The second captures the possibility to transfer funds from an account at one mobile money provider to an account at a different provider. In this paper I focus on the second type, that is, the account-to-account (A2A) interoperability, which reflects the concept of compatibility in the eyes of the consumers as discussed in the literature on network goods.

In this paper, I examine how the introduction of interoperability between multiple mobile money providers affects mobile money adoption by households in Tanzania. I use the staggered introduction of interoperability in the country. In the first place, only three out of four MMPs became interoperable. I also use the variation in network coverage by different mobile network operators (MNOs) to identify districts where introducing interoperability is a relevant policy change (that is, districts that are covered by multiple interoperable MMPs) and districts where introducing interoperability would not matter to the consumer (or would matter to a lesser extent) since only one interoperable MMP covers these areas. I specify a model of demand for mobile money and consider taste for interoperability as a demand parameter to be estimated. The model is similar to the standard differentiated product demand models from the industrial organization literature. In particular, I follow the setup from Berry, Levinsohn and Pakes (2004) by also including interaction terms of the product characteristics with observed household attributes. To estimate the model, I use the Tanzania National Panel Survey data, which contains information on whether households adopt mobile money, and if so, which mobile money providers they choose. To my knowledge, there are no other studies that quantitatively identify the effect of interoperability on mobile money adoption. The only exception is Gilman (2016), also in Tanzania, who however presents only anecdotal evidence based on interviews with some representatives of the concerned MNOs.

This paper connects two strands of literature: the studies on mobile money in developing countries and the empirical literature on network effects in varying contexts. Previous studies have captured network externalities in different industries: ATMs and ACH payment systems (Saloner and

Shepard, 1995; Ackerberg and Gowrisankaran, 2006), spreadsheets (Gandal, 1994; Brynjolfsson and Kemerer, 1996), VCR and CD players (Park, 2004; Gandal, Kende and Rob, 2000), home computers (Goolsbee and Klenow, 2002), videoconferencing systems (Tucker, 2008; Ryan and Tucker, 2012), and mobile phone providers (Birke and Swann, 2010). There is little empirical work on network externalities in the mobile money industry. The only exception is Batista and Vicente (2020) in Mozambique where they use a randomized controlled trial to study the effects of providing mobile money accounts to farmers and two of their closest friends (network intervention) as opposed to giving mobile money accounts only to the farmers. The network intervention increases the overall use of mobile money, which points to the presence of network externalities.

The paper proceeds as follows: Section 2 describes the mobile money industry in Tanzania. In Section 3, I formulate the demand model and discuss the identification strategy. Section 4 presents the data and summary statistics, Section 5 reports the results, and Section 6 concludes.

2 Context: mobile money services in Tanzania

Mobile money penetration in Tanzania is very high, estimated at 53%[4] in 2020 with the total value of transactions at USD 81 billion.[5] The uses for mobile money have also become more complex. Mobile money does not only serve for airtime top-ups and domestic remittances, its initial purposes, but customers are also saving and taking loans through their mobile wallets. According to the 2017 Finscope report[6], 35% of Tanzanians save using mobile money and 4% of Tanzanians take loans using mobile money. The service can also be used for bill payments.

Tanzania has currently six mobile money providers.[7] The first company to launch mobile money services in Tanzania was Vodacom which launched M-Pesa in April 2008. Vodacom was followed by Zantel that launched their product Ezy Pesa in February 2009. Next Tigo introduced Tigo Pesa in August 2010 and Airtel started Airtel Money in April 2012. Finally, the last two products to join the market for mobile money services were Halo Pesa and T Pesa in 2016 and 2017 respectively. The

[4] Mobile money penetration is defined as the number of mobile money accounts divided by the total population.

[5] Tanzania Invest. Tanzania Mobile Money Subscriptions Market Shares 2020. Accessed at: https://tinyurl.com/3nth2256.

[6] Mushi et al. (2017)

[7] GSMA Mobile Money Metrics Deployment Tracker. Accessed at https://www.gsma.com/mobilemoneymetrics/#deployment-tracker.

two major market players are Vodacom and Tigo with market shares of 39% and 30% respectively. The third biggest provider is Airtel with 20%, followed by Halo Pesa at 7%, T Pesa at 3%, and Ezy Pesa at 1%.

In 2013, only one mobile money market allowed for interoperability between accounts of different MMPs. As of 2019, 19 out of 95 markets with live mobile money services were interoperable (Naji, 2020). Tanzania was one of the first countries to implement interoperability. Furthermore, the effort there was industry-led rather than mandated by the government. The discussions about interoperability started in 2012 and the framework received green light from the Bank of Tanzania in 2013. In September 2014, Airtel and Tigo were the first two MMPs to allow cross-net transactions. Zantel became interoperable with Tigo a few months later in December 2014 and Vodacom was the last MMP to connect with the other providers bilaterally in February 2016. In this paper, I focus on the effects of the first introduction of interoperability between Tigo, Airtel, and Zantel.

3 The model

3.1 Basic setup

I model the household choice of mobile money provider by following Berry, Levinsohn and Pakes (2004)[8]. Households choose the alternative that maximizes their utility u_{ijt}. Utility depends on household characteristics and on attributes of each alternative. Not choosing any MMP is included in the model as an outside option. Utility of choosing alternative j for household i in district d and at time t is given by:

$$u_{ijdt} = X_{jdt}\beta_i + \delta_j + \epsilon_{ijdt} \tag{1}$$

where X_{jdt} is a vector of observed product characteristics, δ_j are unobserved, household-invariant characteristics of alternative j (such as cost of adoption), and ϵ_{ijdt} are idiosyncratic preferences of households.

β_i represents the heterogeneous taste of household i for product characteristic k:

[8] Berry, Levinsohn and Pakes (2004) model demand for cars.

$$\beta_{ik} = \beta_{0,k} + Z_{it}\beta_{1,k} \tag{2}$$

where Z_{it} is a vector of observed household characteristics (age of the household head, gender of the household head, wealth index, years of education, residing in a rural area).

Combining the two equations yields:

$$u_{ijdt} = X_{jdt}\beta_0 + X_{ijdt}\beta_1' Z_{it}' + \delta_j + \epsilon_{ijdt} \tag{3}$$

where β_0 captures the average taste for the product characteristics X_{jdt} and β_1 captures heterogeneity in the taste parameter by observed household characteristics.

3.2 Identification

To obtain consistent estimates of β_0 and β_1, the error terms ϵ_{ijdt} need to be independent of the characteristics X_{jdt}. In this paper, I focus only on one mobile money product characteristic: interoperability with other mobile money providers. Therefore, to obtain consistent estimates of β_0 and β_1, the idiosyncratic preference of household i in district d at time t for bundle j (ϵ_{ijdt}) must be uncorrelated with the interoperability status of bundle j in district d at time t.

Interoperability is the only characteristic of mobile money providers that I include in the model. I could include in the model other characteristics such as the the number of mobile money providers in one alternative[9] but due to the reduced choice set (as discussed in the next section) these are difficult to measure. Any alternative-varying characteristics that are not included in the model are captured by the alternative-district fixed effects. Therefore, not including them should not result into a bias of the coefficient on interoperability since these characteristics are not part of the error term.

To be able to estimate the coefficient on interoperability, I exploit the variability in the relevance of this policy change over time and over districts. First, interoperability between Tigo Pesa, Airtel Money, and Ezy Pesa became effective in 2014 and I use two waves of the NPS survey that represent the "before" and the "after" period. Second, there are districts where only one of the interoperable

[9] This is a proxy for adoption cost.

Table 1: Determining the interoperability status of each alternative

	Round 3		Round 4	
	Single MMP	Multiple MMP	Single MMP	Multiple MMP
Not adopt	0	0	0	0
Adopt M	0	0	0	0
Adopt T or A or E	0	0	0	1
Adopt M and (T or A or E)	0	0	0	1

MMPs (Tigo Pesa, Airtel Money, or Ezy Pesa) provide network coverage and districts where two or three interoperable MMPs operate. I refer to these districts as "single MMP" and "multiple MMP" respectively. I assume that interoperability is a relevant feature only for households in the "multiple MMP" districts. By construction, households in the "single MMP" districts derive zero utility from the fact that Tigo Pesa, Airtel Money, and Ezy Pesa became interoperable. The indicator for interoperability is then equal to one if the alternative j contains Tigo Pesa, Airtel Money, or Ezy Pesa and the district d is classified as "multiple MMP", and zero otherwise. Table 1 summarizes the definition of the indicator for interoperability.

For β_0 and β_1 to be consistent, it is therefore necessary that the idiosyncratic preferences of households be independent of the interoperability characteristic. However, it could be the case that households in the "multiple MMP" districts systematically differ in their taste for technological adoption from households in the "single MMP" districts. In particular, we would expect the "multiple MMP" districts to be on average more urban and wealthier since the MNOs are more likely to expand first into places where there is better potential for adoption of mobile phones. However, notice that the unobserved error term ϵ_{ijdt} can be divided into a component that is common to all households in district d for alternative j, into an alternative-level time component, and into a purely idiosyncratic component. That is, $\epsilon_{ijdt} = \zeta_{jd} + \lambda_{jt} + \tilde{\epsilon}_{ijdt}$. Similarly to the approach suggested in Berry, Levinsohn and Pakes (1995) and Berry, Levinsohn and Pakes (2004), I introduce a constant for each alternative in each district and at each time period, which allows me to capture common district-level trends and a time trend for each alternative. Under the assumption that the interoperability indicator is independent of the idiosyncratic preference conditional on ζ_{jd} and λ_{jt}, I am able to consistently estimate β_0 and β_1.

The inclusion of the alternative-district level fixed effects is important even if I allow the parameter of interest to account for observed household heterogeneity. Letting the parameter be a function of observable household characteristics (age of the household head, gender of the household head, education of the household head, wealth, and residence in a rural area) does not capture unobservable household characteristics such as susceptibility for technological adoption. Including alternative-district fixed effects allows me to account for unobserved differences between households living in the "multiple MMP" and "single MMP" districts.

Note that the expression for utility becomes[10]:

$$u_{ijdt} = X'_{ijdt}\beta_0 + X'_{ijdt}\beta_1 Z_{it} + \zeta_{jd} + \lambda_{jt} + \tilde{\epsilon}_{ijdt} \tag{4}$$

Next, I define the probability that a household i chooses alternative j at time t as:

$$p_{ijdt} = Prob[y_{idt} = j] = F(X_{ijdt}, Z_{it}; \beta_0, \beta_1, \zeta_{jd}, \lambda_{jt}) \tag{5}$$

where $y_{idt} = j$ describes the event where household i chooses alternative j and $F(\cdot)$ is a cumulative distribution function. For computational simplicity, let us assume that ϵ_{ijdt} follows Type I extreme value distribution. Then p_{ijdt} takes the mixed logit functional form:

$$p_{ijdt} = \frac{exp(X'_{jdt}\beta_0 + X'_{jdt}\beta_1 Z_{it} + \zeta_{jd} + \lambda_{jt})}{\sum_k exp(X'_{kdt}\beta_0 + X'_{kdt}\beta_1 Z_{it} + \zeta_{kd} + \lambda_{kt})} \tag{6}$$

and can be estimated by maximum likelihood. ζ_{jd} represents the alternative-district fixed effects and λ_{jt} represents the alternative-level time effects. Such specification constrains the time effect to be common across all districts. It could be the case that the time trend is district-varying and including alternative-district-time level fixed effects would lead to a smaller bias in the estimates of β_0 and β_1. However, that would require estimating twice as many parameters and would lead to computational issues due to an insufficient number of observations.

[10] The term δ_j is now captured by the new constants ζ_{jdt}

3.3 Curse of dimensionality and reduction of the alternative set

Since there are four MMPs and the households can choose whether to use services of one, two, three, or even four different firms, the total number of alternatives from which households choose is 16 (including the decision not to adopt). Furthermore, there are 86 districts and two time periods, which brings the total number of parameters to estimate to 1,462 (only counting the constant terms and not the coefficients on interoperability and the interaction terms). This presents a significant computational burden. Also, the majority of the 16 alternatives are chosen by less than 5% of the sample, or not chosen at all, which can further complicate the interpretation of the estimates. Reducing the size of the alternative set alleviates the computational challenge.

Instead of the original 16 alternatives, I consider only four: (i) not adopt, (ii) choose only the dominant, non-interoperable provider (M-Pesa), (iii) choose only non-dominant, non-interoperable provider(s) (Tigo Pesa, Airtel Money, or Ezy Pesa), and (iv) choose both interoperable and non-interoperable providers. The correspondence between the old 16 alternatives and the newly defined alternatives is shown in Table 2. Sample probabilities for these alternatives are shown in Table 3.

Reducing the number of alternatives is a simplification that is necessary given the available data. Adapting the set of alternatives in order to satisfy the key characteristics of choice sets is a common practice in modelling of discrete choice (Train, 2003). In particular, the alternatives must be mutually exclusive and exhaustive. If the decision-maker has can choose between two alternatives that are not mutually exclusive (A and B), then the choice set must be redefined and the alternatives become ”only A”, ”only B”, and ”both A and B”. Generating mutually exclusive combinations in such a way increases the number of alternatives in the model. However, I modify the choice set in the opposite sense, that is, I reduce the set of alternatives by aggregating them. There are several implications of this modeling choice.

The first implication is that I am not able to distinguish between preferences for the specific interoperable providers that are bundled together in alternative 2. The consumers in some districts might be more inclined toward adopting Tigo Pesa rather than Airtel Money. My model cannot capture such preference. The fact that I cannot estimate alternative-level dummies for all different providers separately might affect the estimation of the β_0 and β_1 parameters as well. Too large numbers of alternatives are a common problem for the discrete choice models in marketing[11] and reducing the choice set is an often applied solution to the problem of parameter proliferation. The first method of choice set reduction consists of assuming that consumers form preferences over product attributes rather than over products themselves (Fader and Hardie, 1996; Andrews and Manrai, 1999). This is the method that I am implementing here. The second method consists of using random subsets of full choice sets (Keane and Wasi, 2012). McFadden (n.d.) showed that this method does not affect the consistency of parameter estimates in the absence of consumer heterogeneity. Keane and Wasi (2012) show that in models with unobserved heterogeneity, the bias from using random subsets is only negligible.

By taking the approach of choice set reduction, I am assuming that households do not form preferences for each possible combination of mobile money providers. For example, I am assuming that households do not have a distinct preference for adopting M-Pesa together with Tigo Pesa as opposed to adopting M-Pesa together with Airtel Money. Instead, I am assuming that households have a preference towards adopting the incumbent non-interoperable mobile money provider (M-Pesa) or the interoperable MMPs that are characterized by a smaller market share and delayed entry relative to the incumbent. While this reduction is restrictive in the sense that it does not allow me to capture the inclinations of consumers toward each individual non-dominant MMP separately (Tigo Pesa, Airtel Money, and Ezy Pesa), the alternative approach might be in fact unrealistic. It seems unlikely that households would have a distinct base preference toward each item of the full choice set, for example, toward adopting M-Pesa together with Airtel Money or adopting M-Pesa together with Airtel Money and Ezy Pesa.

Second, a problem arises for some alternative-varying characteristics that cannot be easily included in the model with the reduced alternative set. In particular, estimating the effect of network size on adoption becomes complicated since there is no straightforward way of determining the value for this variable for alternatives that lump multiple mobile money providers together. For instance, choosing alternative 2 means choosing Airtel Money, Tigo Pesa, Ezy Pesa, or any combination of the three. Therefore, the network size that would enter the utility of a given household for alternative 2 depends on which specific bundle within alternative 2 they choose.[12] There is

[11]An example would be consumer goods found in supermarkets such as breakfast cereal with often more than a hundred alternatives constituting the choice set.

[12]That is, whether they choose {T},{A},{E},{T,A},{T,E},{A,E}, or {T,A,E}.

Table 2: Separating adoption bundles into four alternatives

Alternative	0 No adoption	1 Choose dominant, non-interoperable provider only	2 Choose non-dominant, interoperable provider only	3 Choose both
Bundles	{}	{M}	{T}	{M,T}
			{A}	{M,A}
			{E}	{M,E}
			{T,A}	{M,T,A}
			{T,E}	{M,T,E}
			{A,E}	{M,A,E}
			{T,A,E}	{M,T,A,E}

Table 3: Sample probabilities for the four alternatives

Alternative		Round 3	Round 4
0	Not adopt	58.78%	45.31%
1	Adopt Tigo or Airtel or Ezy	12.49%	20.60%
2	Adopt M-Pesa	19.19%	20.50%
3	Adopt M-Pesa and (Tigo or Airtel or Ezy)	9.54%	13.59%

no unambiguous way of how to define the network size of alternative 2 for all households. As a possible extension of this work, one option would be to use the maximum possible network size of each alternative as a proxy for the actual network size of the household's choice.

Estimating the effect of the network size on adoption would allow me to quantify the extent of network externalities in mobile money adoption. As pointed out by Suri et al. (2021), network effects in adoption of mobile money are understudied. The network size could be easily determined for the unrestricted alternative set with the 16 options. However, the issue of endogeneity arises since the error terms in the utility equations (which determine the final adoption decision) are directly correlated with the network size.[13]

[13]Quantifying the network externalities, and especially how these vary with and without interoperability, could be a future extension of this paper.

4 Data and summary statistics

4.1 Tanzania National Panel Survey

For the main analysis I use data from the Tanzania National Panel Survey (NPS) rounds 3 (2012-13) and 4 (2014-15). Both rounds are extracted from the NPS Uniform Panel Dataset (UPD) that consists of a merge between the first four rounds of the NPS. The NPS UPD can be downloaded from the World Bank Microdata Library. The target sample for the first round of the survey consisted of 3,280 households in 410 enumeration areas. The NPS sample is representative of the whole Tanzanian territory with 2,064 households in rural areas and 1,216 in urban areas. The NPS round 2 had a very low attrition rate of 3%. Furthermore, the sample increased to 3,846 households in round 2 due to split households. The attrition rate for round 3 remained exceptionally low at 4% and the sample grew to 5,010 households due to split households. For round 4 the survey sample was redesigned. The new design consisted of a part of the original sample ("Extended Panel") but also of a completely new sample ("Refresh Panel"). The "Extended Panel" consists of 784 households and for the "Refresh Panel" a total of 3,352 households were interviewed.

The NPS includes questions on mobile money services starting from round 2. In particular, the survey instrument asks whether a mobile money service by a given MMP was used, and if so, how often and what were the main types of use of mobile money. The questions are asked at the household level, that is, whether at least one member of the household used these services. I also use the module on household demographics to construct household attributes and the module on household assets to construct a standardized wealth index for the estimation of heterogeneity in the taste for interoperability.

Round 4 of the NPS was collected between October 2014 and November 2015. Given that the interoperability between Airtel Money and Tigo Pesa was launched in September 2014, and between Tigo Pesa and Ezy Pesa in December 2014[14], this round allows me to measure the short-term impacts of interoperability on mobile money adoption.

[14] Tigo Pesa and Ezy Pesa became interoperable two months after the start of the survey which might be problematic for the estimation of the effect of interoperability. However, since Ezy Pesa is used by only 1% of the sample, I do not consider it a significant issue.

4.2 Summary statistics

The data in Table 4 confirm the high mobile penetration in Tanzania reported in other studies. In wave 3 of the NPS (2012-13), 74% of households owned at least one mobile phone. In wave 4 (2014-15) this figure increased to 81%. On the other hand, ownership of a formal bank account seems to stagnate. In wave 3 20% of households had access to a formal bank account, whereas in wave 4 this proportion increased to only 22%. The majority of the sample resides in rural areas (66% in wave 3). However, due to the changes in the sample composition in wave 4 (creation of the "Refresh Panel"), the proportion of the households living in rural areas dropped to 59%. Approximately one fifth of the households are female-headed.

Vodacom's M-Pesa clearly dominated the mobile money market in wave 3. Twenty-nine per cent of households reported using M-Pesa, whereas only 18% used Tigo Pesa, 7% used Airtel Money, and less than 1% used Ezy Pesa. By the time of wave 4, the proportion of households that used M-Pesa increased to 34%, Tigo Pesa's use rate jumped to 25%, and Airtel Money and Ezy Pesa witnessed less dramatic increases to 15% and 1% respectively.

Even though mobile money account ownership is high and a lot of households report having used mobile money services in the last 12 months, the frequency of use is quite low. More than a half of the sample report using mobile money less often than every 6 months. Around 10% of the sample use the service weekly and around 17% use it monthly. Furthermore, there seems to be an overall decreasing trend in the frequency of use of mobile money between waves 3 and 4 of the NPS.

The most common use of mobile money is receiving and sending money. Together with the low frequency of use this seems to suggest that in Tanzania, mobile money indeed serves as an instrument to cope with unexpected shocks as it facilitates the flow of remittances (Riley, 2018). Popular types of use are also airtime top-ups and saving for emergencies.

Finally, adoption choices of households disaggregated by demographic characteristics are shown in Table 5. Specifically, the table shows whether households with different characteristics choose not to adopt mobile money, adopt at least one interoperable provider, or adopt a non-interoperable provider. We can see that interoperable providers are especially chosen by wealthy households with more educated household heads.

5 Results

5.1 Main results

Table 6 shows the estimates of the model specified in equation 6. Column (1) has the estimates for the model without the interaction terms, that is setting β_1 equal to zero. As is the case for nonlinear choice models, the magnitudes of the estimated coefficients do not have a direct interpretation. However, in a mixed logit model signs of the coefficients on alternative-varying regressors are meaningful. Finding a statistically significant coefficient on interoperable (+0.414) means that, on average, households place a positive value on interoperability in their mobile money adoption decision.

Column (2) shows the estimates for the full model including interaction terms with five observed household attributes: age index constructed from the age of the household head, gender of the household head, wealth index, education index constructed from the number of years of education of the household head, and residence in the rural area. The coefficient on interoperability now represents the average effect for a household with average age of the household head, average number of years of education, average total value of assets, male household head, and residing in an urban area. The interaction terms show that interoperability is more valued by younger, more educated, and wealthier households living in urban areas. Female-headed households value interoperability less but the coefficient is not statistically significant.

Table 6: Estimates of β_0 and β_1

Alternative attributes and interaction terms with household characteristics	No interaction terms (1)	Incl. interaction terms (2)
Interoperable	.414	.579
	(.179)	(.194)
Interaction with:		
Age index		-.114
		(.058)
Female HH head		-.089
		(.103)
Wealth index		.225
		(.056)
Educ. index		.465
		(.059)
Rural		-.460
		(.010)

Standard errors are in parentheses. Column (1) shows the results for a model without the interaction terms (imposing $\beta_1 = 0$). Column (2) shows the results for a model with interaction terms. Age index is a standardized index of the age of the household head. Wealth index is a standardized index of the total value of household-owned assets. Educ. index is a standardized index of the number of years of education.

5.2 Discussion of alternative explanations

One of the key assumptions in interpreting the results of this paper as causal effects of interoperability on demand is the fact that the account-to-account (A2A) interoperability is the only change that homogeneously affected the product alternatives containing Tigo Pesa, Airtel Money, and Ezy Pesa between the "pre" period and the "post" period. However, there might have been other factors that could drive the increased adoption of the interoperable MMPs. In particular, the two other drivers of adoption might be marketing campaigns and price wars happening simultaneously with the introduction of interoperability.

It is possible that the MNOs that joined the interoperability scheme would increase their advertising efforts and introduce price promotions in districts with higher potential of growth in the number of new users. The increase in adoption of the interoperable Tigo Pesa, Airtel Money, and Ezy Pesa, and the decrease in the use of Vodacom's non-interoperable M-Pesa could therefore be due to a better visibility of the first two products through more marketing. However, there is evidence that no such advertising and pricing efforts were in place until much later. According to Gilman (2016), Tigo and Airtel had not initiated marketing of the new interoperable services until 2016. Both companies waited to gain "confidence in the technical and operational functionality of the service" before launching their above-the-line and below-the-line marketing campaigns and pricing promotions. The main results of this paper are measured in 2014/15, that is, immediately after the interoperability had been introduced.

Table 4: Summary statistics by survey wave

	(1) Round 3		(2) Round 4	
	Mean	SD	Mean	SD
Use of MM services				
Used M-Pesa	0.29	0.453	0.34	0.474
Used Tigo Pesa	0.18	0.383	0.25	0.431
Used Airtel Money	0.07	0.263	0.15	0.361
Used Ezy Pesa	0.00	0.065	0.01	0.120
Frequency of use				
Daily	0.07	0.256	0.04	0.205
Weekly	0.14	0.346	0.11	0.315
Biweekly	0.05	0.212	0.04	0.206
Monthly	0.17	0.372	0.15	0.352
Every 3 months	0.04	0.193	0.03	0.165
Every 6 months	0.02	0.123	0.01	0.116
Less often	0.52	0.500	0.61	0.488
Never	0.00	0.041	0.00	0.038
Type of use				
Airtime (yourself)	0.41	0.492	0.43	0.495
Airtime (s.o. else)	0.18	0.385	0.19	0.395
Send	0.70	0.459	0.74	0.439
Receive	0.85	0.357	0.88	0.323
Pay	0.14	0.345	0.17	0.379
Save (emergencies)	0.29	0.454	0.35	0.477
Save (everyday expenses)	0.14	0.348	0.14	0.350
Save (large purchases)	0.05	0.219	0.07	0.249
Household-level characteristics				
Female-headed household	0.23	0.418	0.27	0.442
Age of the HH	44.82	15.773	44.53	15.317
Rural	0.66	0.475	0.59	0.493
Receives remittances	0.62	0.486	0.58	0.494
Bank account	0.20	0.402	0.22	0.415
Mobile phone	0.74	0.438	0.81	0.394
N	9998		4961	

Table 5: Choices by demographic groups

		2012-13		2014-15		
		Not adopt	Adopt	Not adopt	Adopt: interop.	Adopt: non-interop.
Gender of HH head	Male	.54	.46	.41	.29	.30
	Female	.54	.46	.42	.27	.31
Age	Below median	.49	.51	.36	.34	.30
	Above median	.59	.41	.46	.23	.31
Education	No educ.	.78	.22	.68	.09	.23
	Some primary	.56	.44	.40	.28	.32
	Some secondary	.29	.71	.24	.45	.32
	Some university	.13	.88	.06	.63	.31
Wealth	1st quartile	.70	.30	.55	.23	.21
	2nd quartile	.54	.46	.39	.34	.28
	3rd quartile	.51	.49	.43	.20	.38
	4th quartile	.42	.58	.27	.38	.35
Owns bank account	No	.65	.35	.50	.21	.29
	Yes	.15	.85	.12	.54	.34
Location	Urban	.25	.75	.21	.46	.32
	Rural	.72	.28	.55	.16	.29
Remittances	No	.58	.42	.47	.26	.26
	Yes	.39	.61	.27	.33	.40

6 Conclusion

Mobile money is an innovative financial product that can help unbanked individuals in developing countries get integrated in the financial system. Mobile money serves as a safer way to send and receive remittances, pay bills, receive welfare payments from the government, save, take loans, and buy insurance. Increasing adoption of mobile money helps increase financial inclusion and thus promotes economic development.

Regulatory framework can be instrumental in driving mobile money adoption. In particular, whether or not to require account-to-account (A2A) interoperability between different mobile money providers has been discussed extensively in the policy sphere. Interoperability is seen as beneficial for the consumers but the industry might be unfavorable to this policy as the individual firms might anticipate a negative impact on their market share. Even though in the case of Tanzania, interoperability was industry-led, there is definitely the scope for this policy to be mandated

In this paper I examine the effects of the account-to-account (A2A) interoperability on adoption of mobile money by different providers using a differentiated product demand model. In Tanzania, the implementation of interoperability was gradual. First only two providers signed a bilateral interoperability agreement, and only two years later the biggest mobile money market player joined the interoperable scheme. I also examine how taste for interoperability varies by household characteristics. I find that, on average, households place a positive value on the interoperability feature of the mobile money products. However, there is heterogeneity across observable household characteristics in how these households value interoperability. In particular, wealthier and more educated households living in urban areas are the ones who value interoperability more.

In the present paper, I was only able to recover the parameters representing the taste for interoperability between different providers in the mobile money market. As a next step, the results could be used in two prediction exercises. First, I could estimate what would happen to demand for mobile money as a result of expansion of coverage of the interoperable MMPs into the "single MMP" districts. Second, I could estimate the effect of the incumbent joining the interoperability scheme on the total mobile money demand. This prediction could be verified against the actual data from round 5 of the NPS.

Empirical studies on what regulatory framework is the most conducive to mobile money adoption are still scarce. More research in this area is needed since a more widespread use of mobile money could have transformative effects on developing economies.

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