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“Interoperability between mobile money agents and choice of network operators: the case of Tanzania”

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Interoperability between mobile money agents and choice of network operators: the case of Tanzania*

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Abstract

In this paper, we study how inter-operability between networks of mobile money agents impacts choices of mobile network operators using a survey data for Tanzania. We use geo-location of respondents to combine the survey data with information on the proximity of mobile money agents. We estimate discrete choice models where consumers' decision to subscribe to a mobile network operator (and mobile money provider) depends on the distance from mobile money agent of this provider. We control for nighttime light intensity to account for geographic differences in economic development and use a set of individual characteristics. We find that the distance to agent has a significant impact on the subscription decision. We use our estimates to conduct counterfactual simulations of imposing inter-operability at the level of mobile money agents. In our alternative scenario consumers can use the closest agent from any mobile money provider. We find that inter-operability at the level of agents has only small impact on the market shares of mobile network operators, where smaller operator marginally gain because their consumers can now use agents of larger providers which tend to be closer. We conclude that interoperability on the level of agents does not have large impact on competition between mobile money operators in the case of Tanzania.

Keywords: Mobile money; M-Pesa; interoperability; nighttime light data

JEL Classification: O12; O16; O18; O33; L86; L96

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1 Introduction

Mobile telecommunications offers a major opportunity to advance economic growth in developing countries. In particular, mobile phones serve as a channel for provision of services which are not available to poor people living in remote areas without infrastructure, such as financial, educational, health, agricultural and other services. Since its launch in Kenya in 2007 under the name of M-Pesa, mobile money services spread rapidly in many countries in Africa and elsewhere. This service allows mobile phone users to transact via a mobile account which is linked to a unique mobile phone number. They can use mobile money for a range of financial services including domestic and international money transfers, saving, taking up loans and insurance services. Mobile money differs from mobile banking where users rely on internet-enabled mobile devices to manage their bank account. In Sub-Saharan Africa, they are provided mainly by mobile network operators who compete with traditional banking services.[1] According to a survey conducted by Research ICT Africa in 2017 in Tanzania, which we use in this paper, 55% of respondents used mobile money as compared to 17% having a bank account. The disproportion between the share of population using mobile money and bank account is greater in other countries in Sub-Saharan Africa.

Even though mobile money is now widely used in Sub-Saharan Africa, digital payments are not yet commonly accepted for everyday purchases at local stores and market places. Thus, mobile money users need to deposit and withdraw cash at cash-in and cash-out points which may be a bank agent, mobile money agent or an automated teller machine (ATM). Mobile money operators need to invest in the network of agents across the country to grow the number of users. A large network and proximity of agents may be a key determinant when choosing a mobile money provider, where first movers and large network operators have a competitive advantage over smaller networks. For example, in 2012 the second mobile network operator in Kenya, Airtel, filed a complaint with the Competition Authority of Kenya (CAK) to force the market leader, Safaricom, to remove the exclusive arrangements with agents and allow access to its network of agents by rival mobile network operators. Airtel also argued that Safaricom was abusing its dominant position with respect to mobile money transfer services by charging twice the amount for mobile cash transfers to Airtel customers than it charged for Safaricom-

[1] By contrast in China, mobile financial services are provided primarily through third-party payment service providers such as Alipay and WeChat using smartphone apps linked to an account at a bank or another financial institution.

to-Safaricom transactions. Safaricom argued in defense that forcing it to open up its agent network would be unfair because it had invested billions of shillings in developing the network. Eventually, in 2014 the CAK ordered Safaricom to open up its M-Pesa agent network to rival mobile money providers.[2] In general, imposing interoperability between different mobile money providers may be a way of mitigating market domination.

There are different levels of interoperability. First, so called account-to-account (A2A) interoperability gives mobile money customers the ability to make a transfer between two accounts held at different mobile money providers or between a mobile money provider and a bank. Second, there may be interoperability at the level of agents who in such case can represent different mobile money providers. Third, interoperability at the merchant level allows consumers to transact at any retailer, regardless of the account held by the merchant.

In this paper, we focus on the interoperability at the level of agents and analyze how it may impact market shares of mobile money providers. We use a rich survey data of 1,200 individuals in Tanzania, which was collected in 2017 by Research ICT Africa. We use geo-location of respondents to combine the survey data with information on the proximity of mobile money agents and mobile network infrastructure, which we obtained from Open Street Map (OSM). We compute distance from the household location to mobile money agents and to towers of mobile networks. We also use nighttime light intensity data to approximate the level of economic development at the location of survey respondents.

We estimate discrete choice models where consumers' decision to subscribe to a mobile network operator (and mobile money provider) depends on the distance from mobile money agent of this provider. In the estimation we control for nighttime light intensity to account for geographic differences in economic development. We also use a rich set of individual characteristics. We find that the distance to agent has a significant impact on the subscription decision. We use our estimates to conduct counterfactual simulations of imposing interoperability at the level of mobile money agents, where in an alternative scenario we assume that consumers can use the closest agent from any mobile money provider. We find that interoperability at the level of agents has only small impact on the market shares of mobile network operators, where smaller operator marginally gain because their consumers can now use agents of larger providers which tend to be closer. We caution that our results hold for Tanzania, where in 2015 the Bank of Tanzania introduced regulation of interoperability between mobile services and mandated non-

[2] Also MTN Uganda, one of the largest MNOs in the country was penalised in 2016 for its refusal to provide services to another mobile money operator EzeeMoney.

exclusivity, which allowed agents to work for many MNOs. To the best of our knowledge this is the first paper which tries to address the question of interoperability between mobile money providers empirically.

The remainder of the paper is organized as follows. In Section 2 we review the relevant literature. Section 3 discusses the development of mobile money services in Sub-Saharan Africa. In Section 4, we discuss the data sets used in our analysis. Section 5 introduces the econometric model and Section 6 presents the estimation results. Finally, Section 7 concludes.

2 Literature Review

Our paper contributes to the following streams of literature. First, mobile money is a two-sided market with mobile money users on one side and mobile money agents on the other side. There are positive network externalities between these two groups, which means that it is beneficial for customers to join the mobile money provider with a greater network of agents. There is a mature body of theoretical literature on interoperability between multi-sided platforms and networks including Katz & Shapiro (1985), Katz & Shapiro (1994); Fudenberg & Tirole (2000); Armstrong (2006); Caillaud & Jullien (2003) and Rochet & Tirole (2003). In particular, Katz & Shapiro (1985) conclude that if the costs of achieving compatibility (or interoperability) are lower for all firms than the increase in profits due to compatibility then the industry move towards compatibility is socially optimal.

Another stream of literature investigates the decisions of firms to inter-operate in markets that are characterised by dominance. For instance, Besen & Farrell (1994) find that if the market is symmetric firms are likely to choose a similar compatibility strategy, but when there is asymmetry firms have conflicting strategies. In particular, late entrants want to inter-operate with the dominant operator. The dominant operator has incentives to block inter-operability to protect its customer base. In related paper, Chen et al. (2009) find that when firms are symmetric, they tend to choose compatibility to expand the market. But when there is asymmetry in the market, a dominant firm may opt for incompatibility.

In general, there is a consensus in the literature that in markets which are characterised by network effects the welfare is maximised when all providers interconnect (see for instance Laffont et al. (1996); Foros & Hansen (2001); Economides et al. (1992); Carter & Wright (1999)). However, in some cases dominant firms may opt not to interconnect to protect its customer base (see Evans & Schmalensee (1995)). In another paper, Katz & Shapiro (1986) study private and social incentives for compatibility in the context of dynamic rivalry and technological progress. They conclude that in the early product life cycle firms may choose product compatibility to avoid intense competition and being driven out of the market. This lowers competition and consumer surplus in the early stage of product life cycle. They also conclude that compatibility intensifies competition in the later stage of market development by eliminating the threat of monopolization. Thus, consumers in the second period derive greater surplus under compatibility than under incompatibility. However, firms in the second-stage may prefer incompatibility to protect their consumer base.

The studies mentioned above do not consider the tradeoff between the benefits of compatibility and the benefits of variety. Farrell & Saloner (1986) take such tradeoff into account and conclude that there may be too much standardization in equilibrium which may be inefficient, especially when unique equilibrium is not a focal point. They further conclude that in a case where a wrong equilibrium is attained less standardization increase variety and consumer welfare. In contrast to Farrell & Saloner (1986), Matutes & Regibeau (1988) show that product compatibility increases consumer welfare by giving consumers the liberty to mix and match products which increases the variety of products. They also show that even in markets that are not characterised by network effects, firms have incentives to produce compatible products. When firms produce compatible products, a decrease in one firm's price increases the sales of other firms producing compatible products.

Doganoglu & Wright (2006) develop a theoretical model to study the effect of product compatibility and multi-homing on competition. Consistent with findings in Katz & Shapiro (1986), they find that consumers enjoy greater network benefits when competing firms make their product compatible. However, their results suggest that the same benefits arise when firms produce incompatible products, but consumers multi-home. They also conclude that multi-homing may reduce competition, as compared to product compatibility.

To the best of our knowledge, there are no empirical studies that investigate the effect of interoperability on competition in the mobile money market. There are few studies which focus on markets such as the PC, software and the video games. For instance, Economides & Katsamakas (2006) study market of PC operating systems and conclude that without interoperability, there may be a winner-takes-all outcome. In another paper, Cennamo & Santalo (2013) empirically analyze the U.S. video game industry and show that when two competing platforms pursue winner-takes-all strategies, the performance of each platform is lower.

Second, our paper contributes to the literature on mobile money. Among these studies, many focus on M-Pesa in Kenya. For instance, Mbiti & Weil (2015) analyze the use and economic impact of M-Pesa in Kenya using two waves of individual-level data on financial access. They find that M-Pesa has a positive impact on individual welfare by promoting banking and increasing money transfers. Jack & Suri (2014) use two waves of about 3,000 households in Kenya to study transactional networks and conclude that in households with M-Pesa users there is more remittance activity than in those without. They also find that households which use M-Pesa are more likely to remit for routine support, credit and insurance purposes. They conclude that mobile money allows households to spread risk more efficiently through deeper financial integration and expanded informal networks. Murendo et al. (2018) assess the effects of social network on mobile money adoption among rural households in Uganda. They find that mobile money adoption is positively influenced by the size of social networks. In another paper, Munyegera & Matsumoto (2016) use data on 846 rural households to analyze adoption of mobile money, remittance activity and household welfare in Uganda. They find a positive and significant effect of mobile money access on household welfare. Similar to Jack & Suri (2014), they conclude that households that use mobile money are more likely to receive remittances than non-user households. They also find that the total value of remittances received by households that use mobile money is significantly higher than for non-user households. In another paper, Gutierrez & Singh (2013) use data on 37,000 individuals from 35 countries to analyze determinants of mobile banking usage. They conclude that a supporting regulatory framework is associated with higher usage of mobile banking in the whole population and among the unbanked.

The papers discussed above rely on surveys of individuals or households. There are also recent studies which apply a randomized controlled trial (RCT) to estimate causal effects of mobile money. Randomized access to mobile money is either given directly to individuals (Batista & Vicente (2013) and Batista & Vicente (2018)) or to small-scale entrepreneurs (Aggarwal et al., 2020). Finally, Economides & Jeziorski (2014) use mobile financial transactions among subscribers of a major mobile phone service provider in Tanzania during three months and to estimate price elasticities for different types of transactions. They find that demand for long-distance transfers is less elastic than for short-distance transfers, which suggests that mobile networks actively compete with antiquated cash transportation systems in addition to competing with each other. They use the demand estimates to provide measures of willingness to pay to avoid carrying cash in the pocket when traveling as well as keeping cash at home. There is only one qualitative paper by Bourreau & Valetti (2015) which provides an assessment of the economic features of mobile payment systems in low income countries. They conclude that mobile money has the potential to drive financial inclusion of poor households at low cost. We contribute to this literature by studying interoperability at the level of mobile money agents to assess how compatibility might impact competition among mobile money providers.

3 Mobile Money and Interoperability

Mobile money services are linked to a unique mobile phone number and enable users to cash-in money using a mobile account called mobile wallet. These services are provided entirely on the mobile networks. Subscribers can use mobile wallet for a range of financial services including domestic and international money transfers, payments of bills, airtime top-up and others. The transactions are settled through the network of agents which is established by the mobile money providers. Mobile banking, on the other hand, are financial services which enable consumers to access bank account, transfer money, make payments and perform other financial operations on their mobile phones. A mobile phone can also serve as virtual bank card, point of sale terminal or an ATM. These services are provided by a bank or other financial institutions in addition to their banking services.

The most common mobile money service in Sub-Saharan Africa is M-Pesa, which was first launched in Kenya in 2007 by Safaricom. Today, M-Pesa is the most popular mobile money service in East African countries including Uganda, Tanzania, Rwanda and Burundi and has been increasingly used in other African countries such as Cote d'lvore, Senegal, Madagascar, Mali, Niger, Botswana, Cameroon, South Africa as well as outside Africa in Jordan and Afghanistan. A number of banks in Africa rolled out a similar service called e-wallet. The difference to M-Pesa in that e-wallet requires the sender to have a bank account and the receiver can only cash-out money at ATMs using their mobile phone number and a pin.[3]

Interoperability

There are different levels of inter-operability. First, so called account-to-account (A2A) inter-operability gives mobile money customers the ability to make a transfer between two accounts

[3]See www.bocra.org.bw

held at different mobile money providers or between a mobile money provider and a bank. This includes person-to-person (P2P) interoperability, i.e., the possibility for customers to make transfers between their mobile money accounts, as well as bank account to mobile money account (B2M) and mobile money account to bank account (M2B) transfers. Second, there is inter-operability at the level of agents who in such case can represent different mobile money providers. Third, inter-operability at the merchant level allows consumers to transact at any retailer, regardless of the account held by the merchant.

In general, A2A interoperability reduces the cost of transactions between people using different mobile money providers. Thus, it should increase the volume of money transfers and overall usage of mobile money. The benefits from interoperability at the agent level are due to sharing large fixed cost of building a network of agents who need to be recruited and trained. This network needs to be maintained by mobile money provider and provided with cash. The agents also need a minimum number of customers and enough liquidity to be viable, which is easier when they serve multiple mobile money providers. Under interoperability the network of agents has a broader reach relative to separate networks, which should further stimulate adoption and usage of mobile money.

In general, GSMA (2014) argues that interconnection is more likely to happen voluntarily if mobile money networks are still small and of similar size. Firms with a strong first-mover advantage, due to an early start and significant investments in rolling out their agent network may be reluctant in opening their network of customers and agents to small competitors. While the short-run effect seems to be negative for larger operators, in the medium run agreeing to interoperability brings advantages, especially if the overall growth potential of the market is large. It may simply be better to be a less-than-dominant operator in a large market than a dominant one in a small market. From a market perspective, a refusal of interoperability by the largest operator can result in a lack of competition, in particular if the number of viable candidates for agents is limited (CGAP 2011). It may be too costly for smaller networks to create their own separate agent network. Thus the refusal of interconnection can freeze a very asymmetric market structure, to the detriment of mobile money customers. In this vein, early dominance of one operator (such as Safaricom in Kenya) may imply that other operators cannot reach critical mass even if they decide to inter-operate among themselves. In this case, it is unlikely that interoperability among wireless carriers will be achieved without direct government intervention.

Mobile Money in Tanzania

In Tanzania, there are seven mobile network operators (MNOs), where as of December 2018 the five biggest players in terms of subscriptions were Vodacom (32%), Tigo (29%), Airtel (25%), Halotel (9%) and Zantel (3%). These five MNOs also compete to provide mobile money services. Vodacom launched its mobile money service, M-Pesa, in April 2008, one year after a successful launch of the same service in Kenya. Also in 2008, Zantel introduced a mobile money service, Z-Pesa, which was upgraded in 2012 and renamed Ezy Pesa. Airtel, the third largest MNO, launched its mobile money service, Airtel Money, in 2009. Finally, Tigo introduced its Tigo Pesa in September 2010 focusing on money transfers. The last entrant Halotel started providing mobile money services called Halopesa in 2016.

The launch of mobile money services in Tanzania was a success and in June 2016 there were 17.3 million mobile money accounts. The MNOs' market shares on mobile money accounts were as follows: Vodacom M-Pesa had 43% of the market, Tigo Pesa 32%, Airtel Money 23%, and finally Zantel Ezy Pesa 2%. The services offered on the mobile money platforms of the MNOs are domestic and international money transfers, mobile payments (e.g., airtime top-ups), and mobile banking services (balance inquiries, withdrawals, deposits and credit services). The number of agents has also increased dramatically over time. According to the Bank of Tanzania (BoT), there were 2,757 agents in Tanzania in 2008. The number of agents increased to 29,095 in 2010 and then to 97,613 in 2012. It further doubled to 203,752 in June 2014 and reached 280,675 in June 2016.

In Tanzania, the payment services are regulated by the Bank of Tanzania, which in 2007 issued guidelines for electronic payment schemes to allow banks and MNOs to offer mobile money services, after clearance from the central bank through a no-objection letter. Interoperability (either at the agent, customer or platform level) was a stated requirement in the draft regulations. However, it was not formally mandated and the BoT had indicated its preference for a market-based solution. In September 2014, Airtel and Tigo reached a bilateral agreement (their off-net transfer services were launched commercially in February 2015). In December of the same year, Tigo and Zantel also signed an agreement on interoperability. And finally, one year later, in February 2016, the market leader, Vodacom, signed bilateral agreements with Airtel and Tigo. By 2016 Tanzania became the first country in the world to achieve full interoperability between all of its mobile money providers.

In general, the approach to competition and interoperability in Tanzania had a positive impact on financial inclusion. The percentage of adults with access to formal financial services, which includes mobile money, increased from 16% in 2009 to 65% in 2017. The percentage of people living within 5km of a financial service provider, which includes mobile money agents, increased from 45% to 86%. The number of mobile money accounts reached 17.5 million in June 2017.

4 Data

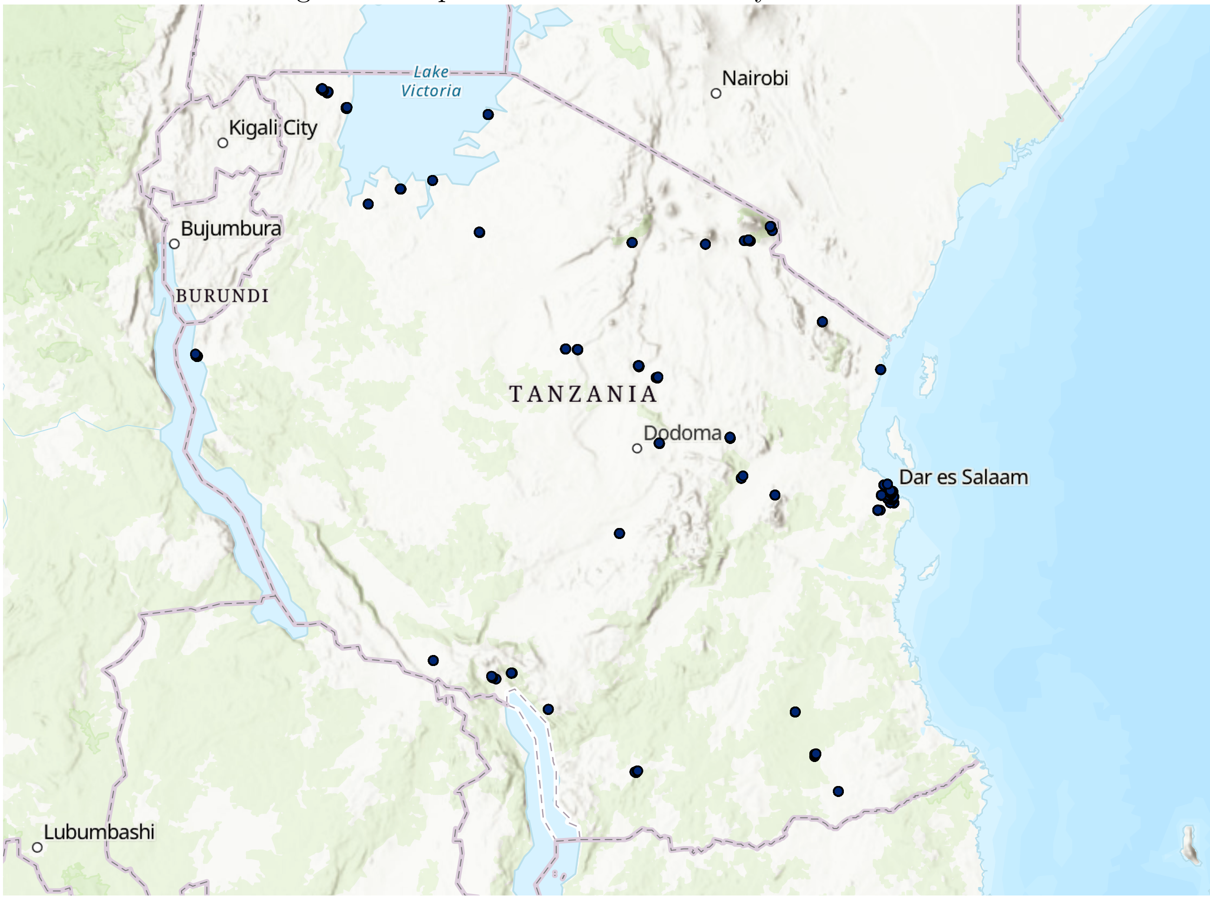
In this paper, we use a representative survey data of approximately 1,200 individuals in Tanzania, which was collected in 2017 by Research ICT Africa. The survey was conducted using electronic Android tablets and an external GPS device to capture the exact coordinates of the household.[4] Figure 1 shows a geographical distribution survey respondents in Tanzania. We use the geographic coordinates to merge the survey with the other data sets including information on the availability and proximity of infrastructure. In particular, we calculate the distance between individuals in our survey and mobile money agents attached to different networks. We focus specifically on Tanzania because there is geo-location information for mobile money agents, which is not available for other Sub-Saharan African countries surveyed by Research ICT Africa, except Kenya. But in Kenya mobile money services are highly dominated by Safaricom, which makes it difficult to study interoperability.

Based on our survey, almost 40% of individuals in Tanzania do not possess a mobile phone (see Figure 2). The dominant mobile money provider is M-Pesa which is served by about half of all mobile money agents in the country, as shown in Figure 2. But the shares of mobile money agents serving Airtel Cash and Tigo Pesa, two other service providers, are non-negligible. There are also relatively few agents that serve the smallest service provider Ezy Pesa. The majority of agents serve only one provider, but about 20% serve two different providers and about 10% serve three different providers.

Figures 3 shows for each operator the distribution of distances to the closest mobile money agent. When only the chosen operators are considered, the average distance decreases. This suggests that the distance to the agent matters when choosing an operator. Ezy Pesa has a very low market share and consequently, many consumers have a high distance to an agent of that operator. For the other operators in Tanzania, the distributions of distances are comparable.

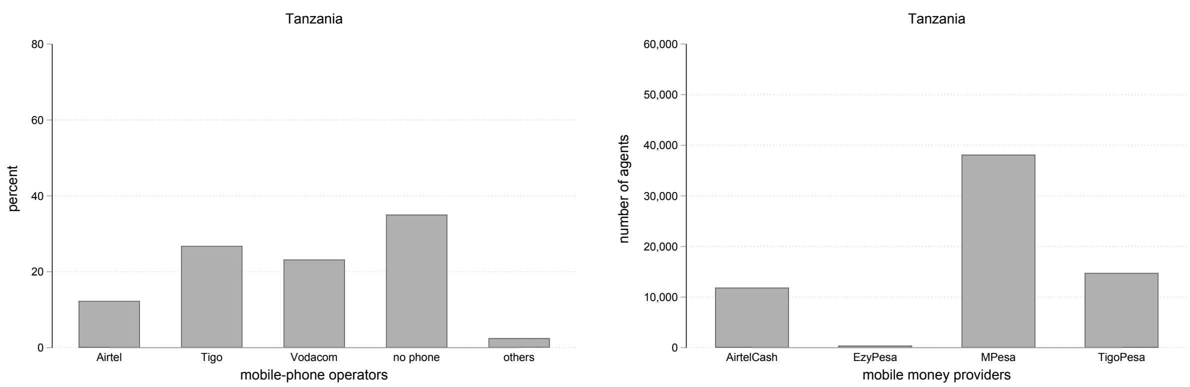
[4] For details on the representativeness, sampling and data collection see https://www.datafirst.uct.ac.za/dataportal/index.php/catalog/765.

Figure 1: Map of Tanzania with surveyed individuals



Notes: Geographic distribution of the surveyed individuals in Tanzania.

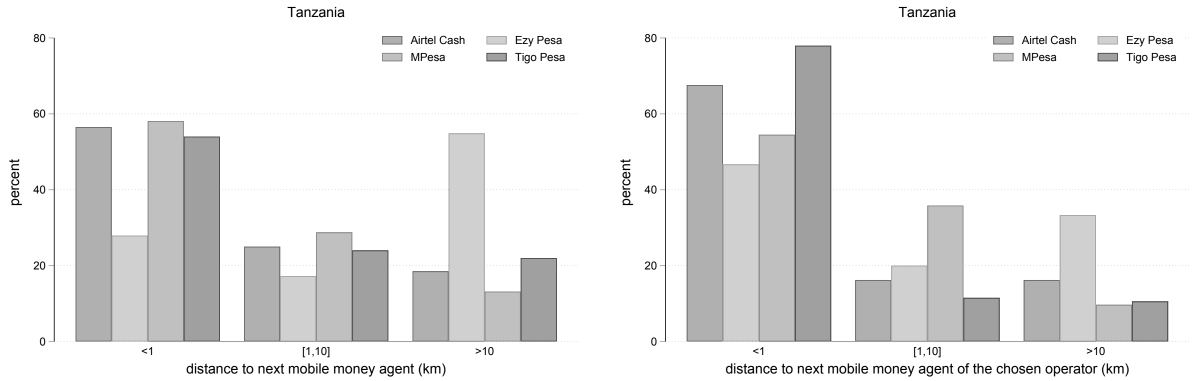
Figure 2: Chosen mobile-phone operator



Notes: Left: The distribution of chosen mobile-phone operators in the survey. Right: The distribution of mobile money agents by network operators.

About 60 percent of the consumers have an agent of any of the providers within one kilometre. When we consider the agents of the chosen provider, this number increases to almost 80 percent and very high distances vanish.

Figure 3: Distance to the closest mobile money agent from each provider



Notes: The distribution of distance to the closest mobile money agent from each provider.

Besides the survey and mobile money agents, we use nighttime light (NTL) emission as a proxy for economic development. This data stems from the Visible Infrared Imaging Radiometer Suite (VIIRS) from the *Suomi* satellite provided by the Earth Observations Group (EOG), Payne Institute for Public Policy. We apply the yearly cloud-free averaged data from 2016. In the earlier economic literature, initiated by Henderson et al. (2011), the Defense Meteorological Satellite Program (DMSP) was used, but the VIIRS data has better quality for the purpose of our study. First, the DMSP was originally used to detect the global distribution of clouds and cloud top temperatures in the early 1970s. Since the establishment of a digital archive in 1992 by the NOAA/NGDC, these nighttime data have been widely exploited by the scientific community. However, the nighttime light data was not created for scientific research as the main purpose, which is different for the VIIRS data. Second, the DMSP was stopped by 2013. So, for more recent data access the VIIRS is the only source. Third, the VIIRS data is more precise in the light intensity as well as in the base area. We exploit light averages at 15 arc-second geographic grids ($\approx 465m \times 465m$ at the equator, or $\approx 465m \times 385m$ at 35 degrees of latitude). Outliers, such as light from aurora, fires, boats, and other temporal lights were filtered out by EOG.

A further database comes from OpenStreetMap (OSM), which is a collaborative effort to set up a free database with geographic information on infrastructure. This database provides among others information about geo-location of mobile money agents and banking facilities.[5] Besides the use of satellite images, users can add information. We downloaded the data from Geofabrik's free download server in December 2019.

The final database on the cell tower location was downloaded from OpenCelliD.[6] Moreover, the date of creation and the kind of technology can be observed: GSM (2G), UMTS (3G), and LTE (4G). We use only the antennas which were constructed before 2017 to make sure that individuals in our survey could use these antennas. For each household, we calculate distance to the closest antenna of each technology.

Table 1 shows the penetration of mobile phones, usage of banking services, NTL data, and distance to infrastructure in Tanzania for the 1,200 surveyed individuals. Mobile phone was owned by 66% of individuals in the sample, where 20% own a smartphone. Moreover, 55% use mobile money, 17% have a bank account and 10% have a credit card. Using mobile money, owning a bank account, and owning a credit card are not mutually exclusive. In Tanzania, mobile coverage of the most basic technology, GSM (2G), is available for almost all individuals (95%), while UMTS (3G) is available for almost two-thirds and the share of individuals with LTE (4G) availability is only 41%. Based on the NTL satellite data, slightly more than half of the individuals in our sample live in places which are not light at night. The light intensity is on average 4.32 with a maximum of 28.

5 The Model

5.1 The Choice of Network Operator

We estimate a number of models for the decision to adopt mobile services from different operators and for usage of mobile money services. First, we estimate a multinomial logit model where consumers choose between different network operators in Tanzania. An individual consumer $i = 1, ..., N$ chooses network operator $j \in J$ when $U_{ij} = \max_{k \in J} U_{ik}$, where we define a standard linear utility which consumer i derives from adopting a mobile phone denoted as:

$$U_{ij} = Z_i \beta_j + \xi_j + \epsilon_{ij} \tag{1}$$

[5]There is also information about geo-location of cities and towns, banks and ATMs, railway stations and bus stops, and of major roads.

[6]https://www.opencellid.org/downloads.php

Table 1: Summary Statistics: Tanzania

VARIABLES	(1) mean	(2) sd	(3) min	(4) p25	(5) p50	(6) p75	(7) max	(8) N
mobile money (0/1)	0.55	0.50	0.00	0.00	1.00	1.00	1.00	1,200
bank account (0/1)	0.17	0.38	0.00	0.00	0.00	0.00	1.00	1,173
credit card (0/1)	0.10	0.30	0.00	0.00	0.00	0.00	1.00	1,173
mobile phone (0/1)	0.66	0.47	0.00	0.00	1.00	1.00	1.00	1,173
smartphone (0/1)	0.20	0.40	0.00	0.00	0.00	0.00	1.00	1,173
light intensity	4.32	6.36	0.00	0.00	0.00	7.00	28.00	1,173
distance to next bank	20.03	29.07	0.03	1.17	5.10	26.51	140.56	1,173
distance to next ATM	24.76	28.41	0.03	2.63	14.19	36.09	110.58	1,173
distance to the road network	0.70	1.21	0.00	0.12	0.28	0.72	7.66	1,173
distance to the electricity grid	15.65	30.09	0.01	1.15	3.63	17.70	167.13	1,173
distance to next railway station	62.65	87.22	0.61	3.32	15.22	105.49	371.65	1,173
distance to next bus stop	14.82	28.19	0.03	0.71	3.46	14.80	139.37	1,173
distance to next town	23.32	18.84	0.01	13.99	20.97	25.96	111.05	1,173
distance to next city	57.92	65.48	0.63	7.42	33.64	111.97	253.34	1,173
LTE (4G) coverage (0/1)	0.41	0.49	0.00	0.00	0.00	1.00	1.00	1,194
UMTS (3G) coverage (0/1)	0.64	0.48	0.00	0.00	1.00	1.00	1.00	1,195
GSM (2G) coverage (0/1)	0.96	0.21	0.00	1.00	1.00	1.00	1.00	1,200

Notes: The table reports summary statistics.

Here Z_i includes a set of individual/household characteristics and infrastructure variables which determine adoption. The alternative-specific coefficients, β_j, are estimated relative to the outside option of not having a mobile phone. The individual-specific valuation for alternative j, i.e., the 'logit error term', is represented by ϵ_{ij}. It is assumed to be identically and independently distributed over network operators and individuals according to the type I extreme value distribution. Finally, ξ_j denotes quality of network operator j, which is estimated as network-specific dummy variable. We do not use prices of mobile services in the estimation because we do not know the exact tariff plan used by individuals. Thus, we cannot estimate price elasticities of demand for mobile services, but ξ_j should control for the differences in average prices of mobile networks. In this regression, we are particularly interested in estimating how distance to mobile money agents impacts network adoption decision.

The assumption on the distribution of the error term ϵ_{ij} allows to formulate standard multinomial logit choice probabilities. The parameters of the model are then estimated using maximum likelihood estimator. We use the estimates to conduct simulations of how enabling agents to serve multiple mobile money providers impacts market shares of network operators.

5.2 The Usage of Mobile Money

Separately to the choice of mobile network operator we estimate adoption of mobile money services. The decision to use mobile money services is made in two stages. In the first stage, consumers choose one from available mobile networks or no mobile access at all. In the second stage, those who subscribed to mobile services decide whether to use mobile money. In the first stage, we focus on the zero-one adoption decision and ignore the decision to subscribe to different network operators. The reason for this is that the decision to use mobile money should not be impacted by the network operator to which individuals subscribe. But also the number of observations in the regressions for separate network operators is small. Thus, the decision problem of consumer i can be written using the following two equations:

$$Y_i = \begin{cases} 1 & \text{if } Y_i^* = Z_i\beta + \epsilon_i > 0 \\ 0 & \text{if } Y_i^* = Z_i\beta + \epsilon_i \leq 0 \end{cases} \tag{2}$$

$$V_i = \begin{cases} 1 & \text{if } V_i^* = X_i\gamma + \varepsilon_i > 0 \\ 0 & \text{if } V_i^* = X_i\gamma + \varepsilon_i \leq 0 \end{cases} \tag{3}$$

where the first equation (2) is similar to the network choice model described above, except that there are only two alternatives. We use the same set of individual/household characteristics and infrastructure variables, Z_i. A mobile network subscription, $Y_i = 1$, is chosen when the utility is greater than zero, $Y_i^* > 0$. The second equation (3) denotes the use of mobile money, which is observed only if $Y_i = 1$. The use of mobile money is determined by individual characteristics and infrastructure variables included in X_i with coefficient γ. The error term is denoted by ε_i and satisfies the condition $E(\varepsilon_i|Z_i, X_i) = 0$. The model is non-parametrically identified from exclusion of some of the variables in the choice equation, Z_i, from the variables in usage equation, X_i. In particular, we consider that the adoption of mobile phones is determined by network coverage, which does not affect usage of mobile money services.

There is a problem with estimating mobile money usage equation (3) when there are unobserved characteristics of the individuals that affect both the network subscription choice and mobile money usage. Then the error term ε_i is not independent of ϵ_i and for a binary usage variable V_i a simple logit or probit estimation is not consistent. Thus, the appropriate likelihood function for the model in equations (2) and (3) and $v_i = 0, 1$ is:

$$L(\theta) = \prod_{i=1}^{n} [Pr(Y_i^* \leq 0)]^{1-Y_i} \cdot [Pr(V_i = v_i | Y_i^* > 0) \cdot Pr(Y_i^* > 0)]^{Y_i} \tag{4}$$

where the parameter $\rho = cov(\epsilon, \varepsilon)$ denotes the covariance of the error terms from both equations and $\theta = (\beta, \gamma, \rho)$ is the vector of parameters to be estimated. Defining univariate c.d.f by $\Phi(Z_i\beta)$ and $\Phi(X_i\gamma)$ and bivariate c.d.f by $\Phi_2(Z_i\beta, X_i\gamma, \rho) = Pr(V_i = 1 | Y_i^* > 0)$ and $\Phi_2(Z_i\beta, -X_i\gamma, \rho) = Pr(V_i = 0 | Y_i^* > 0)$, we can write equation (4) as follows:

$$L(\theta) = \prod_{i=1}^{n} [\Phi(-Z_i\beta)]^{1-Y_i} \cdot [[\Phi_2(Z_i\beta, X_i\gamma, \rho)]^{V_i} \cdot [\Phi_2(Z_i\beta, -X_i\gamma, \rho)]^{1-V_i}]^{Y_i} \tag{5}$$

We use maximum likelihood to estimate the vector of parameters θ.

6 The Estimation Results

First, we estimate how distance to mobile money agents impacts the choice of network operator by means of multinomial logit, as shown in Table (A.1). We find that there is a significant and negative impact of distance, i.e., mobile networks with a smaller network of agents who are further away are less likely to be chosen by consumers. There are also significant differences in the utility of networks, as reflected by significant dummy variables for network operators. These differences may be due to differences in network quality, prices and coverage. We have also interacted network dummy variables with other variables including network coverage by LTE technology, nighttime light data, having bank account, credit card and access to electricity. There are significant differences between network operators with respect to these variables. Interestingly, M-Pesa is less likely to be chosen in areas where consumers are closer to LTE towers (within 5km), which may be due to substitution with mobile banking that generally requires mobile broadband. Also, M-Pesa and Tigo Pesa are less likely to be chosen in areas which are dark in terms of nighttime data and thus less developed economically. Overall, consumers who have bank account are more likely to use mobile phones as well as consumers with access to electricity with some differences across network operators. Furthermore, adoption of mobile phones depends on the age of consumers, their income level, martial status, number of people in the household, education level and professional occupation.

Next, we estimate two-stage Heckman selection model, where the first stage is the decision to adopt a mobile phone, as shown in Table (A.1). This decision is also negatively influenced by the distance to mobile money agents. There is less adoption in areas in which consumers are further away from the agent. The impact of proximity of LTE towers is negative as in the multinomial logit but insignificant. There is less adoption of mobile phones in dark areas in terms of nighttime light data again due to economic underdevelopment. Individuals who have bank account, credit card and access to electricity are more likely to use mobile phones. As before, adoption of mobile phones is influenced by consumer characteristics such as age, income, marital status, education and professional activity.

In the second stage, we estimate the determinants of mobile money usage for individuals having mobile phones. Distance to mobile money agents does not have a significant impact on mobile money usage after people get a mobile phone. They may decide to get mobile phones to be able to use mobile money in first place. There is less usage of mobile money in dark areas in terms of nighttime light data, which are less economically developed. There is some variation with respect to mobile money usage by age group, where younger people tend to use it more. There are no differences with respect to income level, which suggests that all income groups rely on mobile money transfers. However, people with more education tend to use mobile money more. Distance to banking facilities such as an ATM does not impact mobile money usage.

We use our model to conduct counterfactual simulations, where we assume that agents can serve multiple mobile money providers. Thus, the distance to an agent is the minimum distance to agent from any of the network operator. We show how market shares of mobile operators change in Table (A.2). The smallest network operator, Ezy Pesa, increases its market share from 1.7% to 2.4% (an increase by 44.4%), but the effect on market concentration is marginal. M-Pesa's market share declines from 23.9% to 23.5%. There is also a marginal increase in take up of mobile phones. We conclude that interoperability on the level of agents does not have large impact on competition between mobile money operators. However, as discussed in Section 3, in Tanzania there was full interoperability between all mobile money services since 2016. Thus, our estimates are specific to a market in which consumers can transfer money between different operators. The distance to mobile money agents may be less important in such case.

7 Conclusion

In this paper, we study how interoperability between networks of mobile money agents impacts choices of mobile network operators using a survey data of 1,200 individuals from different geographic locations in Tanzania, which was collected in 2017 by Research ICT Africa. We use geo-location of respondents to combine the survey data with information on the proximity of mobile money agents and mobile network infrastructure, which we obtained from Open Street Map (OSM). We compute distance from the household location to mobile money agents and to towers of mobile networks. We also use nighttime light intensity data to approximate the level of economic development at the location of survey respondents.

We estimate discrete choice models where consumers' decision to subscribe to a mobile network operator (and mobile money provider) depends on the distance from mobile money agent of this provider. We control for nighttime light intensity to account for geographic differences in economic development and use a set of individual characteristics. We find that the distance to agent has a significant impact on the subscription decision. We use our estimates to conduct counterfactual simulations of imposing interoperability at the level of mobile money agents. We assume that in an alternative scenario consumers can use the closest agent from any mobile money provider. We find that interoperability at the level of agents has only small impact on the market shares of mobile network operators, where smaller operator marginally gain because their consumers can now use agents of larger providers which tend to be closer. We conclude that interoperability on the level of agents does not have large impact on competition between mobile money operators. However, we caution that our results hold for Tanzania, where in 2015 the Bank of Tanzania introduced regulation of interoperability between mobile services and mandated non-exclusivity, which allowed agents to work for many MNOs. Thus, our estimates are specific to a market in which consumers can transfer money between different operators. The distance to mobile money agents may be less important in such case.

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Appendix A

Table A.1: Multinomial logit / Probit / Heckman selection model

	Multinomial logit					Probit	Heckman	
	phone	airtel	halotel	tigo	vodacom		phone	mobile money
dist_agent	-0.012**					0.001	0.003	0.001
	(0.005)					(0.005)	(0.005)	(0.003)
Network dummies		-2.808***	-4.631***	-4.631***	-1.922***			
		(0.654)	(1.191)	(1.191)	(0.606)			
LTE<5km		-0.137	-0.009	-1.297***	0.141	-0.332		-0.181
		(0.446)	(1.045)	(0.384)	(0.384)	(0.349)		(0.208)
Dark		-0.458	-0.262	-0.827**	-1.004***	-0.915***	-0.532**	-0.519***
		(0.429)	(1.078)	(0.350)	(0.369)	(0.319)	(0.209)	(0.192)
Bank account		1.279**	2.528***	2.040***	1.494***	1.694***	0.264	0.900***
		(0.613)	(0.799)	(0.554)	(0.554)	(0.533)	(0.290)	(0.268)
Credit card		2.022*	0.978	1.652	1.629	1.721	0.360	0.813
		(1.145)	(1.334)	(1.116)	(1.115)	(1.102)	(0.383)	(0.522)
Electricity		0.511**	0.284	0.861***	0.576***	0.638***	-0.052	0.376***
		(0.243)	(0.575)	(0.211)	(0.209)	(0.175)	(0.179)	(0.103)
age group 1	0.072					0.043	0.644*	0.033
	(0.356)					(0.356)	(0.340)	(0.211)
age group 2	0.703**					0.700**	0.553	0.418**
	(0.354)					(0.354)	(0.364)	(0.212)
age group 3	0.805**					0.826**	0.612	0.503**
	(0.370)					(0.370)	(0.381)	(0.221)
age group 4	0.290					0.292	0.660*	0.187
	(0.391)					(0.391)	(0.375)	(0.236)
age group 5	0.646*					0.659*	0.630	0.416*
	(0.390)					(0.391)	(0.405)	(0.235)
income group 1	0.682*					0.700*	-0.476	0.372
	(0.406)					(0.408)	(0.429)	(0.246)
income group 2	1.558***					1.574***	-0.236	0.865***
	(0.435)					(0.437)	(0.463)	(0.259)
female	0.699					0.705	0.433	0.443
	(0.696)					(0.698)	(0.434)	(0.387)
married	0.535***					0.567***	-0.069	0.338***
	(0.188)					(0.189)	(0.182)	(0.110)
hh size 2	-0.345					-0.337	-0.199	-0.217
	(0.341)					(0.340)	(0.280)	(0.198)
hh size 3	-0.511*					-0.496*	-0.214	-0.301*
	(0.286)					(0.285)	(0.244)	(0.164)
primary	0.487*					0.515*	0.416	0.322**
	(0.267)					(0.266)	(0.291)	(0.159)
secondary	1.044***					1.091***	0.730*	0.669***
	(0.308)					(0.307)	(0.377)	(0.183)
tertiary	1.196***					1.266***	0.819*	0.795***
	(0.414)					(0.413)	(0.430)	(0.240)
employed	0.619*					0.613*	0.323	0.372*
	(0.333)					(0.333)	(0.261)	(0.193)
self_employed	0.482*					0.407	0.316	0.247
	(0.275)					(0.275)	(0.235)	(0.163)
housework	-0.506*					-0.555*	0.328	-0.323*
	(0.287)					(0.288)	(0.264)	(0.172)
student	-1.001***					-1.000***	-0.622*	-0.580***
	(0.357)					(0.358)	(0.356)	(0.210)
retired	-0.854*					-0.888*	0.397	-0.494*
	(0.454)					(0.455)	(0.442)	(0.268)
ATM	0.392					0.403	-0.094	0.220
	(0.274)					(0.275)	(0.187)	(0.157)
Constant						-1.116*	0.583	-0.660*
						(0.587)	(0.922)	(0.351)
Athrho							-0.173	
Observations	5,950					1,190	1,190	1,190

Table A.2: Simulated market shares

Provider	current	simulated	change
Airtel Cash	12.7%	12.7%	-0.2%
Ezy Pesa	1.7%	2.4%	44.4%
M-Pesa	23.9%	23.5%	-1.5%
Tigo-Pesa	27.2%	27.3%	0.2%
None	34.5%	34.1%	-1.2%