Network infrastructure, mobile financial technologies and financial inclusion: Micro-spatial evidence from rural Nigeria

1. Introduction

The recent rapid evolution of mobile financial technologies (e.g. mobile money, hereafter, MOMO)[1] has shaped the view that mobile phones can play a crucial role in promoting financial inclusion among the unbanked populations of developing countries (Munyegera and Matsumoto, 2016; Gabor and Brooks, 2017). Despite the undisputed potential for innovations in information and communication technology (ICT), such as MOMO, to foster financial access and financial inclusion across developing regions of the world, one of the cited reasons why branchless banking technologies have failed to diffuse is lack of adequate ICT infrastructure (Bayes, 2001; Rotchanakitumnuai and Speece, 2003; Diniz et al., 2012). We would argue that the adoption and penetration of branchless banking technologies may well depend on the diffusion and reliability of the underlying ICT infrastructure (Donovan, 2012; Demirgüç-Kunt et al., 2018). After all, the practical use of these technologies requires infrastructure for connectivity. Even in public policy settings, the diffusion of ICT infrastructure is considered an important enabler of financial technology adoption and development. For instance, a recent financial inclusion policy published by the Central Bank of Nigeria (CBN) stated, inter alia:

The CBN recognizes the importance of Mobile Network Operators (MNOs) in the operations of mobile money and appreciates the criticality of the infrastructure they provide

(Central Bank of Nigeria (CBN), 2015, p.3).

[1] MOMO is a form of branchless electronic wallet technology that enables people to receive, store and spend money using their mobile phones.

Yet, the extent to which the spread of ICT infrastructure shapes the adoption of branchless banking technologies remains largely unclear. This is particularly crucial for many Sub-Saharan African countries where the acute dearth of ICT infrastructure and high incidence of financial exclusion co-exist (Neto et al., 2005; Buys et al, 2009; Allen et al., 2016; Demirgüç-Kunt et al., 2018). Plausibly, the role of ICT infrastructure diffusion matters more for widening financial access in developing countries, relative to the more advanced economies (see Djankov et al, 2007; Beck and Demirgüç-Kunt, 2008). For instance, the latest figures from Internet World Stats[2] indicate that the share of population with access to internet infrastructure in Africa remains lowest at 36%. Secondly, sub-Saharan Africa is still home to a large percentage of the world's unbanked population as the World Bank Findex database shows that 17% of the world's unbanked are in sub-Saharan Africa (World Bank, 2015). These challenges are a far cry from the situation in developed countries where access to important infrastructure that drive banking technologies have been available for several decades.

Against this background, this paper provides the first econometric assessment of the relevance of ICT infrastructure diffusion to the adoption of branchless banking technologies. Our contribution to existing literature is fourfold. Firstly, we draw on a unique dataset that combines geo-referenced cell tower[3] information with a spatially explicit microdata that is large but local in nature[4]. Hence, our measure of broadband infrastructure is micro-spatial in nature, i.e., it is based on the density or concentration of cell sites at the street-level. This micro-spatial approach renders more nuanced and invaluable insights on whether/how spatial

[2] https://www.internetworldstats.com/stats.htm

[3] Cell towers are equipment that facilitate wireless communication between phones and mobile networks. They consist of radio antennas, transceivers, amplifiers, etc.

[4] The closest relatives to this study are Buys et al. (2009) and Hodler and Raschky (2017). However, they differ significantly from this study as they employ country-level data to investigate mobile technology diffusion in the context of the digital divide and ethnic politics, respectively.

proximity or access to ICT infrastructure shapes the penetration and diffusion of banking technologies at the local/individual-level. It is well established that urban areas or populations benefit from higher concentration of ICT infrastructure, which may enable social learning and adoption of ICT technologies (Liu and San, 2006). These geographic disparities in infrastructure access are very much relevant to the urban-rural gap in financial access.

Secondly, our focus on rural areas is timely, given that the majority of unbanked individuals in the developing world reside in rural areas (Dymski, 2009). We reckon that the promotion of financial inclusion requires a deep understanding of factors that may mitigate rural financial exclusion. One of such crucial factors is mobile network coverage, the foremost modern technology in rural areas of developing countries (Aker and Mbiti, 2010). Moreover, Nigeria is the largest economy in Africa and one that epitomizes the settings of high financial exclusion and dearth of infrastructure (Economist, 2016; Demirguc-Kunt, et al., 2018). For example, according to the 2017 Global Findex report, Nigeria's bank penetration rate stands at 44%, with a significant urban-rural gap in financial inclusion. The 2017 Global Findex report also indicates that a substantial proportion of the globally unbanked adults reside in Nigeria. Hence, Nigeria provides a plausible case study for investigating the role of ICT infrastructure diffusion in shaping the adoption of branchless banking technology in the context of broadening financial access.

Thirdly, our analysis is informed by a nationally representative survey from which over 15000 responses from rural households were used for our analysis. To the best of our knowledge, this survey dataset is by far and away one of the largest technology surveys ever used to analyse technology diffusion and usage in sub-Saharan Africa. Besides, from a policy viewpoint, our study informs key policies in Nigeria regarding the management of mobile money operators, some of which are generally applicable to other developing countries of the world.

Fourthly, we find that the rapid penetration of mobile financial technologies, such as MOMO, can foster financial inclusion among the unbanked population in the case of this geo-referenced study of Nigeria. Our results show that a higher concentration of network infrastructure for mobile financial technologies contributes to the adoption and usage of MOMO services. In addition, we uncover evidence to suggest that the propensity to adopt MOMO services is greater among non-account holders, who represent the financially excluded, relative to account owners, who characterise financial inclusion. These findings can help to inform national governments in designing domestic policies for enhancing financial inclusion; the findings can also provide a guide for multilateral development organisations who are exploring intervention modalities as part of country programmes for financial technologies that can help overcome exclusion from formal financial services. Specifically, our findings highlight the strong prospects for technology-driven financial inclusion in rural areas, where mobile phone coverage often represents the foremost modern technology diffusion with potential to dislodge entrenched financial exclusion. Moreover, our results are robust to instrumental variables analysis, alternative measures of mobile infrastructure, among several other robustness tests.

The remainder of the paper is organized as follows. In the next section, we undertake a review of the relevant literature on MOMO adoption and usage. Section 3 discusses the data that underpins our analysis, while section 4 explains the econometric specification underpinning our analysis as well as the estimation variables. Section 5 presents our main estimation results while section 6 draws the main conclusion of the paper.

2. Literature Review

In the last decade, MOMO has had profound influence on the delivery of financial services to the unbanked across the world. However, empirical economic research on this relatively new phenomenon is quite sparse as shown by the review conducted by Aron (2018). The few MOMO studies can however be split into two main strands. The first strand represents studies offering insights into the socio-economic outcomes of MOMO adoption. For instance, Kikulwe et al. (2014) showed that MOMO adoption positively influenced household welfare among Kenyan farmers by facilitating the receipt of remittances from relatives and friends. Other studies have argued that MOMO usage increases the likelihood of borrowing and receiving remittances (Munyegera and Matsumoto, 2016) and the propensity of individuals to save for health emergencies (Ky et al., 2018). Furthermore, Sekabira and Qaim (2017) found that the adoption of MOMO contributed to higher household off-farm incomes and consumption levels among coffee farmers in Uganda. The authors found that MOMO helped farmers to access high-value markets outside their local regions resulting higher off-farm incomes. Similarly, studies have also portrayed how MOMO usage mitigates negative shocks to individual users and households (Jack and Suri, 2014; Blumenstock et al., 2016; Riley, 2018), while other socio-economic benefits include the use of MOMO to successfully facilitate anti-poverty initiatives among households (Aker et al., 2016; Suri and Jack, 2016).

Aside the socio-economic benefits of MOMO adoption, a second strand of studies has also sought to understand the determinants of MOMO usage – although these are far and few in between compared to the first strand. In fact, the current study identifies only three published economic studies in this space (Aker and Mbiti, 2010; Munyegera and Matsumoto, 2016 and Murendo et al., 2018). For instance, using data collected among Kenyans, Aker and Mbiti

(2010) showed that users of M-Pesa were more likely to be wealthier, better educated, located in urban areas of the country, and 'already banked', thereby suggesting the notion that MOMO facilitates financial inclusion may be in doubt. However, perhaps a more focused reflection of MOMO adoption determinants is the study by Murendo et al. (2018) who used a sample of only rural households in Uganda. Their study showed that social networks represent an important target for policy-makers aiming to promote MOMO technology among the poorest unbanked households. Munyegera and Matsumoto (2016) showed that MOMO adoption among households in were associated with the level of education, a result which chimes with the findings of Aker and Mbiti (2010). Other determinants observed in Munyegera and Matsumoto (2016) that positively influenced MOMO adoption includes mobile phone ownership and income. Finally, a more recent study by Yermack (2018) adopts a different tack by exploring the linkages between legal systems and fintech applications. The study finds that the adoption of fintech applications and their subsequent contributions to driving financial inclusion appear to be greater for economies with common law systems.

In view of the potential range of benefits resulting from MOMO adoption, the need to elucidate current understanding of adoption antecedents is even more crucial. There is thus an impetus for further research to explore MOMO adoption factors beyond the influence of socio-economic factors. One key factor which we explore in this study is the role of mobile infrastructure diffusion which we would argue represents perhaps a key underlying mechanism of MOMO adoption. In any case, access to network technology represents an important determinant for the socio-economic development (Aker and Mbiti, 2010; Demirguc-Kunt et al., 2018). Indeed, technology can play a transformative role, creating possibilities for improving life conditions (Avgerou, 2008), especially in the African contexts. MOMO usage may well depend on the diffusion and reliability of the underlying technology or infrastructure (Donovan, 2012; Demirgüç-Kunt et al., 2018). Therefore, MOMO usage is very likely to be influenced by the availability of underlying technology (that is, mobile infrastructure). Thus, we formulate the first hypothesis as follows:

H1: *We expect the diffusion of mobile infrastructure to have a significant and positive effect on MOMO usage.*

A second critical issue explored in our research centres on the extent to which mobile financial technology could drive financial inclusion. From the viewpoint of the policymaker, the concern is whether mobile financial technologies can help overcome exclusion from formal financial services. If this notion holds, then there should be discernible differences in the adoption and usage of MOMO services among bank account owners (who represent financial inclusion) and non-account holders (i.e., who are excluded from formal financial services). If the adoption differs across both groups, it could reinforce the idea of a technology-driven financial inclusion. In addition, it could plausibly complement the literature on how reduced financial constraint could shape small business productivity, especially as relating to the possibility for entry to new export markets (extensive margin) and value of such exports (intensive margin)[5] . Consequently, we formulate the second hypothesis on the differences in MOMO adoption for account-holders vs non-account holders:

H2: *We expect the propensity to adopt MOMO services to be greater among non-account holders relative to account owners.*

[5] Berman and Héricourt (2010) and Besedeš and Prusa (2011) provide useful discussion relating financial access to financial development and extensive/intensive margins.

3. Data

We draw on two data resources. The first is a nationally representative market survey carried out by Africa's largest mobile operator, MTN[6] during April-July 2018. The market survey covers 15107 rural dwellers across 362 localities (i.e., villages or towns); selected using a three-stage stratified random sampling procedure. The survey data contains information on MOMO subscription, GPS location of frequent use (home/work/school), individual-level characteristics such as monthly expenditure, age, gender, religion, educational qualifications, employment and marital status. The second resource is OpenCellID database[7], the world's largest repository of cell tower sites (Hodler and Raschky, 2017).

3.1 Defining MOMO

Our main dependent variable pertains to measures of MOMO adoption or usage. To this end, we employ two different definitions of MOMO usage. Firstly, we convert each respondent's subscription information into a dummy indicator variable for the adoption/use of MOMO services. Beyond mere subscription, we apply responses on the frequency of usage, hence, we use information provided in the follow-up question: "*How often do you use the service?*". We then calculate the dependent indicator variable as a dummy that takes the value 1 if MOMO services are used at least on a monthly basis. Secondly, we use network activity data to calculate the monthly average transaction value for each subscriber. This allows for a more precise measure of usage which enables us to capture the reliability and confidence of users in MOMO services. As shown in Table 1, the data indicates that 9.2% of survey participants have MOMO accounts, falling roughly in the same ballpark as the 6% MOMO penetration reported by the

[6] https://www.mtn.com/
[7] http://opencellid.org

2017 Global Findex Database. The average MOMO transaction value is 1600 Naira (approximately $4.5), roughly 8% of the national minimum wage of 18,000 Naira (approximately $50) per month. While the distribution of the two dimensions would suggest MOMO's modest status across rural Nigeria, it also indicates its strong potential to drive financial inclusion, given that 62% of the sample have no bank accounts, yet 84% of them have a mobile phone.

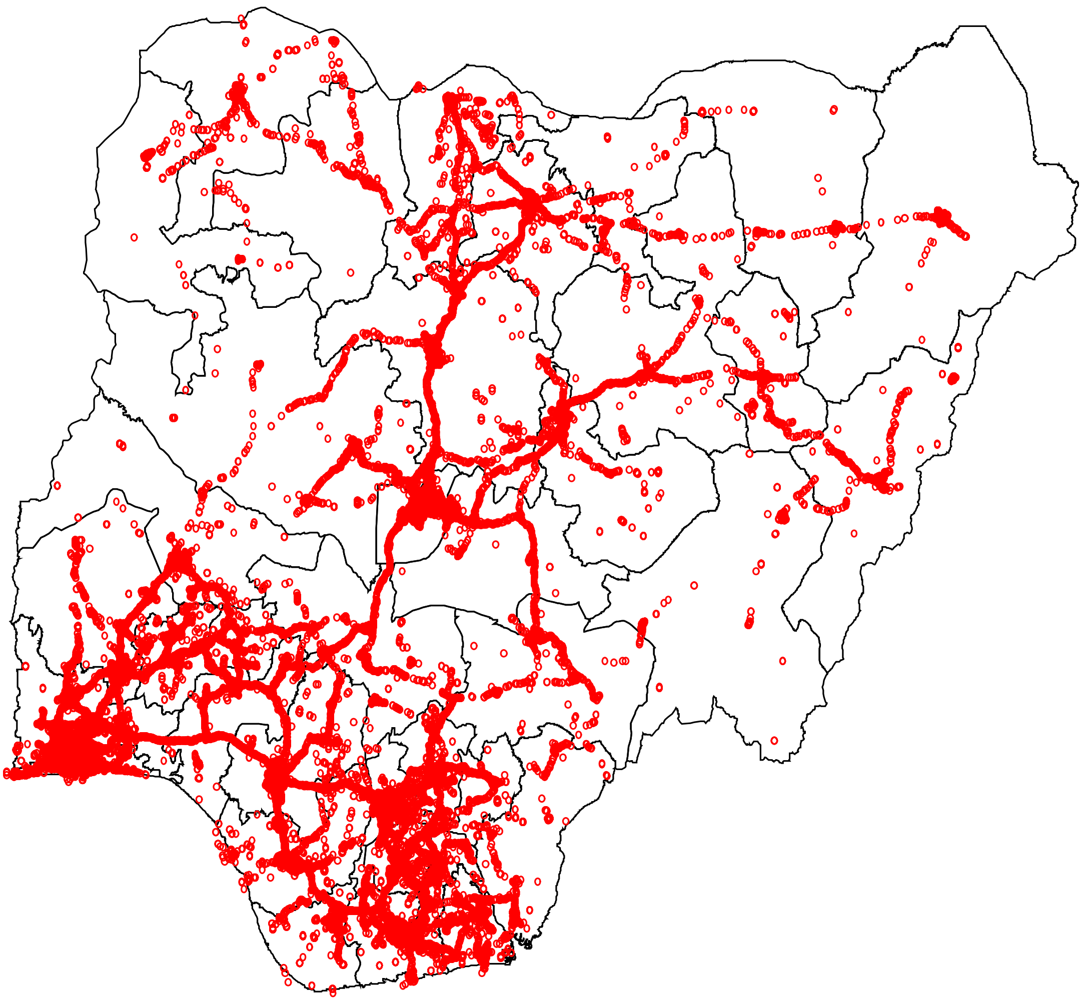
3.2 Microspatial infrastructure diffusion

To examine the effect of mobile phone infrastructure on MOMO usage, we are interested in a metric that captures individual-level access to mobile technology. Hence, we favour a proxy that reflects the prevalence of cell tower infrastructure at the individual-level. We calculate this variable using information from our two data sources in four steps. Firstly, because the MTN survey contains geo-referenced information (i.e. longitude and latitude) of each respondent's residence, our main task was aimed at constructing a spatial database on the prevalence of mobile network infrastructure around sampled respondents. Hence, inspired by Hodler and Raschky (2017), we extract and map the cell tower locations from OpenCellID (http://opencellid.org), the world's largest database of global GPS positions (longitude and latitude). See Figure 1.

Secondly, we extract and map the street-level locations from the survey data. We identified 198485 cell sites within Nigeria as at May 2018 when we accessed the the data[8].

[8] Our subsequent checks underscore the stability (little change) in the number of cell sites data. This is not surprising given that mobile network rollout is based on CAPEX plans which are implemented annually or on a 2-3year basis.

Figure 1: GPS locations of cell towers



Source: OpenCellID data plotted using STATA's *"spmap"*

Thirdly, we validate the cell sites information using operator base transceiver station (BTS) data from MTN. We find the OpenCellID data to be consistent with the MTN data. Hence, to use both data for our purpose, we link them by overlaying the towers map with the dwelling location map[9]. Finally, we calculate the prevalence of mobile cell sites as the total number of active cell towers within 10km of each respondent's dwelling. The premise for the 10km radius is that most of the sampled respondents are either farmers or artisans whose farms/workstations are within a maximum distance of 7.1 kilometers of their dwellings. This implies that all the survey respondents spend a significant proportion of their daily lives within an 8km radius. We experiment with an alternative (lower) radius of 8km in order to test the sensitivity of our results to variations in radial specification. Hence, we compute a micro-spatial mobile infrastructure variable as the total number of cell towers within 10km radius of each frequent use location.

3.3 Other control variables

We include a range of economic, demographic, social and geographical variables in line with existing literature on ICT adoption and usage (e.g. Rappoport, et al., 2001; Goldfarb, 2006; Nevo et al., 2016). Most of these variables are derived from the survey data. To control for income, we use the sum of monthly expenditure on five basic items (food, rent, fuel, clothing and healthcare). We also control for educational attainment, age, gender, religion, employment and marital status. We expect monthly expenditures (our proxy for income) to affect MOMO adoption/usage positively. The probability of this adoption decision is also likely to rise for more educated individuals. However, the need for MOMO services, however, may fall for older and unemployed respondents.

We add a gender variable as an additional characteristic, given that the preferences and decisions of men are more dominant than the preferences of their spouse(s) in patriarchal

[9] The spatial linking and radial calculations are undertaken using the "Geonear" facility available in STATA application software.

societies (Bulte, et al., 2016; Majlesi, 2016). Similar considerations can be extended to the marital status of an individual on the adoption of ICT services. In terms of age, one could argue that, whereas younger individuals may have lower income, they tend to demonstrate a greater degree of technological affinity (Hübler and Hartje, 2016). Finally, technology adoption decisions are often shaped by religious reasons, as some religious beliefs may restrict the adoption of conventional banking or technological products (La Porta, 1997; Fungáčová, et al., 2017). Hence, we control for the religious beliefs of each sampled individual.

Table 1: Descriptive statistics for all variables used in the study

Variable	Obs.	Mean	Std Dev.	Min.	Max.
Cell towers within 10 km	15107	478.136	1219.034	2	2501
MOMO use (=1, zero otherwise)	15107	0.092	0.288	0	1
MOMO value (Naira)	15107	1601.322	7784.734	0	180000
Average expenditure (Naira)	15107	19445.06	28527.23	0	68235.8
Age (years)	15107	34.967	19.293	18	76
Education (years)	15107	10.191	4.511	0	18.1
Male (1, zero otherwise)	15107	0.546	0.498	0	1
Married (1, zero otherwise)	15107	0.476	0.499	0	1
Unemployed (1, zero otherwise)	15107	0.13	0.336	0	1
Christian (1, zero otherwise)	15107	0.592	0.492	0	1
Water as fraction of land use (%)	15107	1.255	5.918	0	50.687
Distance to state capital (km)	15107	64.887	48.772	1.413	225.826

4. Empirical specification

To gauge the relevance of mobile infrastructure empirically, we estimate the following model[10]:

[10] We estimate eqn. [1] for the whole sample as well as for bank account holders and non-account holders

$$mm_{ij} = \alpha_j + \beta infrastructure_{ij} + \gamma X_{ij} + \varepsilon_{ij} \qquad [1]$$

where individuals and localities are indexed by i and j, respectively, mm_{ij} is an indicator variable for MOMO usage or its average monthly transaction value. Due to the 9.2% penetration rate for MOMO, 90% of the sample have zero transaction values. Hence, in the transaction value estimations, we use an inverted hyperbolic sine function (IHS) transformation (see Burbidge, et al., 1988). Furthermore, due to the left censoring of 90% of the data, we also estimate Tobit regressions[11]. The locality effects α_j ensure that we only exploit variation in mm_{ij} based on the differences across individuals, rather than across localities. The coefficient of interest, β, measures the association between mm_{ij} and $infrastructure_{ij}$, the microspatial infrastructure variable. To ensure that β indeed captures the impact of mobile infrastructure, rather than other contemporaneous characteristics, we include a vector of controls, X_{ij}, whose parameters are given by the vector γ. ε_{ij} is the error term.

We estimate [1] via a cross-sectional probit or least squares model. In both cases, we extend our analysis to address the possible endogeneity of cell tower locations. Network operators will plausibly locate cell towers in certain areas, based on viability (e.g. population size) and geographic (e.g. landforms, proximity to cities) considerations (Buys, et al., 2009). Therefore, we employ landforms (water as fraction of land cover) and distance between each street-level coordinate and their state capitals as instruments.[12] Our identifying assumption is that both instruments influence the location of the tower infrastructure by telecommunication operators. The premise is twofold. First, state capitals are major cities that embody core economic hubs,

[11] See Section 5 for further details.
[12] State capital coordinates are from Nigerian Bureau of Statistics. Landform data are taken from the Global Land Cover dataset: https://lta.cr.usgs.gov/glcc/globdoc2_0.

such that market viability and connectivity often diminished in direct relation to the distance from such cities. Hence, we hypothesize that greater physical distance between a locality and the state capital city will result in lower spatial concentration of cell towers in the given locality. Secondly, a landform dominated by larger waterbodies invariably implies less land surface or physical structures for mounting towers.

Finally, we would argue that both instruments are uncontroversial since they are exogenously determined by nature. Moreover, they do not directly affect individual-level MOMO use, except through their impact on $infrastructure_{ij}$. At the same time, the distance variable is a good proxy for regional economic viability, given that capital cities embody core economic hubs, such that income/development often diminishes in direct relation to the distance from capital cities (Gallup, et al., 1999).

5. Results

5.1 Baseline results

Tables 2 and 3 present the marginal effects of the infrastructure variable and other control variables on MOMO usage, derived from probit and linear specifications of [1], respectively. As shown in Table 2, our estimations cover the entire data sample, as well as sub-samples based on bank account ownership. In the first column for each sample, we regress MOMO measures on the cell infrastructure variable without any controls or locality effects. In the second columns, we add the X_{ij} controls and locality effects, α_j. The third columns contain the IV regressions where we control for the endogeneity of mm_{ij} using the distance and landform instruments. Panel C presents the first stage OLS estimates. The coefficients on both instruments have the expected negative sign and are statistically significant at conventional levels. Greater distance to capital cities and larger coastal landforms[13] is associated with lower concentration of cell towers. The Kleibergen-Paap F-statistic strongly rejects the null of weak instruments, while the Hansen *J*-test statistics indicate that the over-identifying restrictions are valid. The importance of the IV approach is also evident from the sizeable differences between the IV and non-IV coefficients, which indicate downward bias in the non-IV estimates.

Due to the cross-sectional nature of our data, we interpret these results as associations. Turning to the mobile infrastructure coefficients, the full sample probit and linear regressions indicate a positive and largely statistically significant infrastructure effect on MOMO use, with the exception of the expanded OLS model. Specifically, the average marginal effect for the full sample IV-probit indicates that cell towers within a 10km radius increase the probability of MOMO use by 6.4%, which corresponds to an increase in the likelihood of MOMO adoption from around 9.2% to around 15.6% in an average respondent. This effect is significant at 1% and is identical to the estimates for the financially excluded (non-account holders) in the data sample. For account holders, the cell tower coefficients unsurprisingly lose statistical significance, as MOMO is likely to be more relevant to the needs of financially excluded individuals. These results show that the diffusion of network infrastructure for mobile financial technologies have a significant and positive effect on MOMO usage, as predicted in Hypotheses 1. The results suggest that diffusion of mobile technology is strongly and positively associated with mobile money usage.

Further, the linear regressions for MOMO transaction values in Table 3 generally corroborate the results of the probit versions, albeit with relatively weaker statistical significance. Again, the full sample and non-account holder results indicate a positive and

[13] Intuitively, larger water forms simply connote less land or physical structures for mounting cell towers.

significant effect of cell infrastructure on MOMO transactions, while the coefficients for account holders remain statistically insignificant. Focussing on the IV estimates, the results indicate that a 10% increase in mobile cell towers within 10km of each respondent leads to a 1.5% (2.3%) increase in MOMO transaction values in the full (non-account holder) sample, albeit these effects are only significant at the 10%-level. These results show that the propensity to adopt MOMO services is greater among non-account holders (the financially excluded) relative to account holders (who represent financial inclusion), as predicted by Hypothesis 2. The results therefore present evidence to support the argument that mobile financial technology can drive financial inclusion, specifically by helping overcome exclusion from formal financial services.

In general, these results are economically important. Specifically, it is well known that network coverage is usually the first modern technology of any kind in rural areas of developing countries of the world (Aker and Mbiti, 2010), hence, the availability of network infrastructure and access is likely to play a crucial role in the adoption and usage of MOMO services. This finding is robust to alternative MOMO definitions and model specifications (probit and linear). Therefore, we would argue that failure to control for this network infrastructure effect could well result in significant omitted variable bias. After all, the potential penetration of any financial technology is strongly dependent on the availability of ancillary infrastructure to support practical use.

Table 2: Mobile infrastructure diffusion and MOMO usage- Probit estimates

Der var: Prob (mm_{ij})	**Full Sample**			**Non-account holders**			**Account holders**		
Panel A	**Probit**	**Probit**	**IV-Probit**	**Probit**	**Probit**	**IV-Probit**	**Probit**	**Probit**	**IV-Probit**
$infrastructure_{ij}$	0.014***	0.008***	0.064***	0.015***	0.009***	0.051***	0.001	0.0002	0.020
	[0.002]	[0.001]	[0.014]	[0.003]	[0.003]	[0.016]	[0.000]	[0.003]	[0.032]
$expenditure_{ij}$		0.010***	0.078***		0.019***	0.110***		0.0001	0.007
		[0.001]	[0.008]		[0.002]	[0.008]		[0.0003]	[0.036]
age_{ij}		0.012***	0.094**		-0.035***	-0.196***		0.0007	0.101
		[0.005]	[0.038]		[0.007]	[0.049]		[0.0011]	[0.116]
$married_{ij}$		0.009	0.071		0.009	0.054		-0.0001	-0.008
		[0.006]	[0.047]		[0.011]	[0.053]		[0.0009]	[0.141]
$education_{ij}$		0.016***	0.363***		0.047***	0.263***		0.0011	0.138*
		[0.008]	[0.071]		[0.013]	[0.060]		[0.0009]	[0.082]
$male_{ij}$		0.027***	0.219***		0.028***	0.156***		0.0002	0.024
		[0.005]	[0.038]		[0.007]	[0.041]		[0.0007]	[0.123]
$christian_{ij}$		0.022***	0.178***		0.009	0.052		0.0010	0.128
		[0.006]	[0.051]		[0.009]	[0.058]		[0.0009]	[0.134]
$unemployed_{ij}$		-0.026***	-0.206***		-0.024**	-0.132*		0.0008	0.010
		[0.008]	[0.063]		[0.011]	[0.077]		[0.0012]	[0.163]
Der var: $infrastructure_{ij}$									
Panel C				**First stage OLS estimates**					
$distance_{ij}$			-1.278***			-1.299***			-1.277***
			[0.094]			[0.109]			[0.094]
$water\_frac_{ij}$			-0.052***			-0.048***			-0.242**
			[0.003]			[0.003]			[0.114]
Kleibergen-Paap F-statistic			361.09			286.56			94.37
Hansen *J*-test [p-val]			0.326			0.169			0.727
Locality effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Number of localities	362	362	362	362	362	362	362	362	362
Number of observations	15107	15107	15107	9410	9410	9410	5697	5697	5697

Notes: Standard errors in parenthesis are clustered at the locality-level. ***, **, and * indicate statistical significance at the 1%, 5% and 10%-level, respectively

Table 3: Mobile infrastructure diffusion and MOMO usage- Linear regression estimates

Der var: mm_{ij}	Full Sample			Non-account holders			Account holders		
Panel A	**OLS**	**OLS**	**2SLS**	**OLS**	**OLS**	**2SLS**	**OLS**	**OLS**	**2SLS**
$infrastructure_{ij}$	0.134***	0.034	0.146*	0.133***	0.124*	0.232*	0.010	-0.007	-0.014
	[0.018]	[0.035]	[0.086]	[0.027]	[0.074]	[0.133]	[0.007]	[0.006]	[0.009
$expenditure_{ij}$		0.070***	0.070***		0.143***	0.144***		0.013*	0.013*
		[0.005]	[0.005]		[0.008]	[0.008]		[0.007]	[0.007]
age_{ij}		0.127***	0.124***		-0.284***	-0.288***		0.001	0.001
		[0.042]	[0.042]		[0.066]	[0.066]		[0.020]	[0.020]
$married_{ij}$		0.078	0.081		-0.012	-0.011		0.006	0.006
		[0.066]	[0.066]		[0.101]	[0.101]		[0.027]	[0.027]
$education_{ij}$		0.187***	0.187***		0.153***	0.152***		0.015**	0.014**
		[0.016]	[0.016]		[0.027]	[0.027]		[0.007]	[0.006]
$male_{ij}$		0.236***	0.237***		0.183***	0.186***		0.007	0.007
		[0.048]	[0.049]		[0.070]	[0.069]		[0.026]	[0.026]
$christian_{ij}$		0.417***	0.417***		0.341**	0.341**		0.042	0.042
		[0.103]	[0.102]		[0.144]	[0.144]		[0.065]	[0.065]
$unemployed_{ij}$		-0.178	-0.178***		-0.096	-0.098		0.018	0.018
		[0.058]	[0.058]		[0.106]	[0.105]		[0.025]	[0.025]
Der var: $infrastructure_{ij}$									
Panel C				**First stage OLS estimates**					
$distance_{ij}$			-1.278***			-1.299***			-1.277***
			[0.094]			[0.109]			[0.094]
$water\_frac_{ij}$			-0.052***			-0.048***			-0.242**
			[0.003]			[0.003]			[0.114]
Kleibergen-Paap F-statistic			361.09			286.56			94.37
Hansen *J*-test [p-val]			0.328			0.321			0.977
Locality effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Number of localities	362	362	362	361	361	361	360	360	360
Number of observations	15107	15107	15107	9410	9410	9410	5697	5697	5697

Notes: Standard errors in parenthesis are clustered at the locality-level. ***, **, and * indicate statistical significance at the 1%, 5% and 10%-level, respectively.

Turning to the other variables, we note across Tables 2 and 3 that the coefficients on the control variables are consistent with theoretical expectations although some of them are not statistically significant at conventional levels, especially for the account holder sample. Across the board, income (i.e. expenditure) has a positive impact on MOMO usage in both the probit and linear specifications. Similarly, a consistently positive influence on MOMO usage is observed for education, male and Christian variables. However, the coefficients on age and unemployment are mixed. For instance, for the full sample age has a positive and significant effect on MOMO usage but this effect turns negative, yet significant for the non-account holders. Nevertheless, the negative coefficient of age for the financially excluded (i.e. non-account holders) is consistent with the argument that technology affinity and adoption diminish with age. Although the unemployment coefficient turns positive and insignificant for account holders, the negative sign on the full sample and account holder sample is consistent with *a priori*.

5.2 *Robustness tests*

So far, we have positive and significant relationship between mobile network infrastructure and the adoption/use of MOMO services. To check the robustness of our results, we conduct further analyses using an alternative infrastructure measure (5km radial specification) and Tobit regressions. The 5km infrastructure variable allows us to test the sensitivity of our results to the radial specification on the cell tower range, while also catering to the possibility that the initial 10km radial specification might be too wide. Furthermore, apart from offering a more localised measure of the infrastructure diffusion, a smaller radial specification can be viewed as a quality-adjusted measure of the infrastructure variable given that signal quality, a key determinant of communication technology usage, is shaped by the physical proximity of users to network connections (Neto, et al., 2005; Grimes, et al., 2012).

As we stated earlier, 90% of our data on MOMO usage are censored to the left, due to the modest levels of MOMO penetration in Nigeria. This problem is particularly relevant for the MOMO transaction values with a large mass of zeros, which means that the dependent variable in the linear regression is constrained and clustered, such that linear regression estimates on our whole data sample or the unclustered portion could be biased and inconsistent. Hence, we estimate Tobit regressions in order to addresses the left censoring of the transaction value regressions.

Tables 4 and 5 present the re-estimated 5-km radial specifications of the probit and linear regression, respectively. The coefficients across all re-estimated models are qualitatively similar to the baseline results, indicating that our findings are robust to variations in the radial specification of the mobile infrastructure variable. Finally, in Table 6, we present the Tobit regression estimates. Again, the Tobit regressions do not qualitatively affect our results.

Table 4: Probit results with 5km radius for infrastructure

Der var: Prob (mm_{ij})	**Full Sample**			**Non-account holders**			**Account holders**		
Panel A	**Probit**	**Probit**	**IV-Probit**	**Probit**	**Probit**	**IV-Probit**	**Probit**	**Probit**	**IV-Probit**
$infrastructure_{ij}$	0.016***	0.009***	0.075***	0.074***	0.011***	0.059***	0.001	0.0002	0.029
	[0.002]	[0.002]	[0.013]	[0.012]	[0.003]	[0.016]	[0.001]	[0.0003]	[0.031]
$expenditure_{ij}$		0.010***	0.077***		0.019***	0.110***		0.0001	0.007
		[0.001]	[0.008]		[0.002]	[0.008]		[0.0002]	[0.036]
age_{ij}		0.012**	0.094**		-0.035***	-0.196***		0.0001	0.102
		[0.005]	[0.038]		[0.008]	[0.049]		[0.0013]	[0.116]
$married_{ij}$		0.009	0.073		0.010	0.054		-0.0001	-0.007
		[0.006]	[0.047]		[0.009]	[0.053]		[0.0012]	[0.142]
$education_{ij}$		0.045***	0.361***		0.047***	0.262***		0.0011	0.138*
		[0.009]	[0.071]		[0.016]	[0.060]		[0.0016]	[0.082]
$male_{ij}$		0.028***	0.222***		0.028***	0.158***		0.0002	0.027
		[0.005]	[0.038]		[0.007]	[0.041]		[0.0001]	[0.123]
$christian_{ij}$		0.023***	0.184***		0.010	0.059		0.0010	0.131
		[0.006]	[0.049]		[0.011]	[0.057]		[0.0014]	[0.131]
$unemployed_{ij}$		-0.026***	-0.206***		-0.023	-0.131*		0.0010	0.099
		[0.008]	[0.063]		[0.015]	[0.077]		[0.0014]	[0.163]
Der var: $infrastructure_{ij}$									
Panel C				**First stage OLS estimates**					
$distance_{ij}$			-1.404***			-1.424***			-1.394***
			[0.096]			[0.108]			[0.104]
$water\_frac_{ij}$			-0.123***			-0.119**			-0.239**
			[0.003]			[0.003]			[0.119]
Kleibergen-Paap F-statistic			1362.794			1220.903			91.909
Hansen *J*-test [p-val]			0.328			0.350			0.759
Locality effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Number of localities	362	362	362	361	361	361	360	360	360
Number of observations	15107	15107	15107	9410	9410	9410	5697	5697	5697

Notes: Standard errors in parenthesis are clustered at the locality-level. ***, **, and * indicate statistical significance at the 1%, 5% and 10%-level, respectively.

Table 5: Linear results with 5km radius for infrastructure

Der var: mm_{ij}	Full Sample			Non-account holders			Account holders		
Panel A	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	OLS	2SLS
$infrastructure_{ij}$	0.149***	0.065*	0.132*	0.157***	0.151**	0.212*	0.009	-0.002	-0.013
	[0.019]	[0.038]	[0.077]	[0.028]	[0.070]	[0.117]	[0.007]	[0.007]	[0.008]
$expenditure_{ij}$		0.070***	0.070***		0.143***	0.143***		0.013*	0.013*
		[0.005]	[0.005]		[0.008]	[0.008]		[0.007]	[0.007]
age_{ij}		0.126***	0.125***		-0.285***	-0.287***		0.001	0.001
		[0.042]	[0.042]		[0.066]	[0.066]		[0.020]	[0.020]
$married_{ij}$		0.078	0.080		-0.011	-0.010		0.006	0.006
		[0.066]	[0.066]		[0.101]	[0.101]		[0.027]	[0.027]
$education_{ij}$		0.187***	0.187***		0.153***	0.153***		0.015**	0.015**
		[0.016]	[0.016]		[0.027]	[0.027]		[0.007]	[0.006]
$male_{ij}$		0.237***	0.239***		0.186***	0.189***		0.007	0.007
		[0.048]	[0.048]		[0.070]	[0.069]		[0.026]	[0.026]
$christian_{ij}$		0.417***	0.417***		0.342**	0.342**		0.042	0.042
		[0.103]	[0.102]		[0.144]	[0.144]		[0.065]	[0.064]
$unemployed_{ij}$		-0.179***	-0.178***		-0.095	-0.095		0.018	0.018
		[0.058]	[0.058]		[0.105]	[0.105]		[0.025]	[0.025]
Der var: $infrastructure_{ij}$									
Panel C				**First stage OLS estimates**					
$distance_{ij}$			-1.404***			-1.424***			-1.394***
			[0.096]			[0.108]			[0.104]
$water\_frac_{ij}$			-0.123***			-0.119**			-0.239**
			[0.003]			[0.003]			[0.119]
Kleibergen-Paap F-statistic			1362.794			1220.903			91.909
Hansen *J*-test [p-val]			0.331			0.339			0.975
Locality effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Number of localities	362	362	362	361	361	361	360	360	360
Number of observations	15107	15107	15107	9410	9410	9410	5697	5697	5697

Notes: Standard errors in parenthesis are clustered at the locality-level. ***, **, and * indicate statistical significance at the 1%, 5% and 10%-level, respectively

Table 6: Tobit estimates

Der var: mm_{ij}	Full Sample			Non-account holders			Account holders		
Panel A	**Tobit**	**Tobit**	**IV-Tobit**	**Tobit**	**Tobit**	**IV-Tobit**	**Tobit**	**Tobit**	**IV-Tobit**
$infrastructure_{ij}$	1.191	1.403	2.835**	1.784	2.296**	2.895**	-8.965***	-7.490***	0.533
	[1.076]	[0.982]	[1.217]	[1.213]	[1.056]	[1.200]	[0.048]	[0.037]	[2.600]
$expenditure_{ij}$		3.662***	3.671***		4.295***	4.302***		1.213***	1.102
		[0.419]	[0.421]		[0.411]	[0.412]		[0.023]	[1.392]
age_{ij}		3.648***	3.601***		-5.560***	-5.587***		2.922***	3.418
		[1.299]	[1.301]		[1.516]	[1.515]		[0.068]	[4.121]
$married_{ij}$		2.189	2.196		1.538	1.537		1.278***	3.511
		[1.573]	[1.577]		[1.619]	[1.622]		[0.135]	[5.433]
$education_{ij}$		11.890***	11.871***		7.926***	7.915***		6.111***	5.984
		[2.464]	[2.463]		[1.819]	[1.821]		[0.056]	[3.692]
$male_{ij}$		6.921***	7.011***		4.435***	4.476***		3.041***	-1.341
		[1.326]	[1.329]		[1.304]	[1.306]		[0.159]	[5.356]
$christian_{ij}$		6.914***	6.921***		6.626*	3.629*		7.730***	6.193
		[2.120]	[2.125]		[2.201]	[2.205]		[0.158]	[4.935]
$unemployed_{ij}$		-7.104***	-6.983***		-4.393*	-4.381*		7.485***	-0.474
		[2.275]	[2.265]		[2.505]	[2.502]		[0.157]	[6.762]
Der var: $infrastructure_{ij}$									
Panel C				**First stage OLS estimates**					
$distance_{ij}$			-1.278***			-1.299***			-1.277***
			[0.094]			[0.109]			[0.094]
$water\_frac_{ij}$			-0.052***			-0.048***			-0.242**
			[0.003]			[0.003]			[0.114]
Kleibergen-Paap F-statistic			361.09			286.56			94.37
Hansen *J*-test [p-val]			0.326			0.169			0.727
Locality effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Number of localities	362	362	362	362	362	362	362	362	362
Number of observations	15107	15107	15107	9410	9410	9410	5697	5697	5697

Notes: Standard errors in parenthesis are clustered at the locality-level. ***, **, and * indicate statistical significance at the 1%, 5% and 10%-level, respectively.

6. Conclusion and policy implications

This paper has undertaken the first ever investigation, to the best of our knowledge, of the extent to which the diffusion of mobile financial technologies, such as MOMO, can foster financial inclusion among the unbanked population in developing countries. The paper has drawn on two large geo-referenced datasets for Nigeria, in order to investigate two specific hypotheses: the diffusion of mobile infrastructure has a significant and positive effect on MOMO usage; the propensity to adopt MOMO services is greater among non-account holders (financially excluded) relative to account owners (financially included).

We find that the diffusion of network infrastructure significantly and positively influences MOMO usage. In other words, the likelihood of adopting MOMO is significantly dependent on the users' spatial proximity to network infrastructure. Encouragingly, this relationship is stable among unbanked individuals. Hence, adopting a network-driven financial inclusion strategy seems to be a plausible imperative in developing countries. Furthermore, this result supports prior research that have portrayed how the diffusion of relevant infrastructure influences the use of different technologies (e.g. Angst, et al., 2010; Weber and Kauffman, 2011). Moreover, from a policy perspective, our result corroborates recent efforts by the Central Bank of Nigeria (CBN) through the national financial inclusion strategy (NFIS), to *"…ensure that over 80% of the bankable adults in Nigeria have access to financial services by 2020…reducing the exclusion rate to 20% by 2020"* (CBN 2018, p. 2).

A key policy implication raised by this study is whether and how the prevalence of network infrastructure engenders MOMO usage among rural unbanked communities. This also speaks to the possibility for mobile technology to help overcome financial exclusion. In addition, to our knowledge, this is the largest empirical research conducted on MOMO usage to date within sub Saharan African. Moreover, by drawing on a nationally representative sample of rural dwellers in Nigeria, a country with one of the largest unbanked populations, the results from this study could potentially deepen our insight on MOMO adoption in a wider developing country context.

Specifically, our results also have implications for the fintech industry in Nigeria which is currently dominated by mainstream banks and a growing number of privately-funded investors. Recent reports have revealed how the largest mobile telecom company operating in Nigeria are in the process of obtaining independent banking licenses in Nigeria by 2019, with other industry mobile operators in the country likely to follow[14]. This suggests that mobile operators in country now view the provision of financial services such as the delivery of peer-to-peer payments as one they could exploit (CBN 2018), leading possibly to the rise of agency banking in Nigeria. We would argue that such moves are likely to change the delivery of financial services in Nigeria, given that these mobile operators are also primarily responsible for the installation of telecom infrastructure across the country. In addition, we suggest that policies aimed at ensuring financial inclusion among the unbanked communities should be encouraged by easing regulatory bottlenecks that may be faced by infrastructure service providers.

[14] https://www.vanguardngr.com/2018/10/mobile-money-telcos-push-aggressively-for-payment-banking-services-license/

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