The Techno Frenemies: Phones versus computers in sub-Saharan Africa

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Abstract

As technology flows across the world, the rate of technological penetration declines in developing areas. At the same time, demand for phones has swollen up in developing areas such as Africa. These trends remain unexplained. This study aims, therefore, to explore the hidden link between these two anomalies with an emphasis on ICT demand in 21st Century Africa.

Introduction

Developing regions, especially Sub Sahara Africa, have baffled scientists because of the unexpectedly high demand for mobiles[1]. Mobiles close the ICT gaps that plague most remote developing countries. Simultaneously, other technological devices also diffuse into these regions. However, non-mobile technological diffusion slows down before it fully penetrates developing markets. Part of the reason may lay in the demand for mobiles. Mobiles overcome many of the current structural impediments in remote regions. For instance, in a village with limited electricity, a mobile can last a day with power and is rechargeable via alternative methods e.g. bicycle dynamo generators. Moreover, mobiles (and telephones[2]) are easily diversifiable in use. Diversified phone[3] services e.g. mobile banking, deters the need for more expensive, fragile and riskier gadgets such as PCs[4]. Thus, my main question tests whether there is any relationship between demand for phones and PCs among individuals and businesses in Africa.

To answer my question, my paper explores the complementary/substitutionary link between demand for phones and PCs. My null hypothesis is that demand for phones has no statistically significant effect on demand for PCs at both home and firm level. My alternative hypothesis is that demand for phones has a statistically significant negative effect on demand for PCs at homes, and a statistically significant positive effect on demand for PCs at firms. To analyze these expectations, I collect panel data on common ICT gadgetry and demographics. For my empirical framework, I do a regression of percentage PC demand on percentage phone

[1] Phone that uses radio waves for transmission
[2] Phone that uses a metal wire or fiber optic telephone line for transmission
[3] Phone = Telephones + Mobiles
[4] Personal computers (and commercial computers for the sake of this paper)

demand and related control variables such as GDP per capita etc. I also incorporate new variables in secondary regressions. I then validate my findings using various robustness tests.

My paper utilizes the phone as the main independent variable because it is shown to dominate the ICT market in Africa as reported in The Economist (2007). Additionally, I focus on sub-Saharan Africa since it is the only developing area that is most beset by challenges that hamper ICT penetration, thus is perfect for studying the natural impact of phones on PCs.

ICT data on Africa is limited. Thus, my temporal limits are 2000-2015 for homes and 2005-2015 for firms. Additionally, I only analyze 48 of the 50 sub Saharan African nations; excluding Western Sahara and Reunion which have no data. I acquire demographic data from the World Bank Africa Development Indicators | Databank and World Development Indicators databases. I also derive ICT data from the International Telecommunication Union (ITU) database. However, these datasets also have missing data. Consequently, my sample may be limited in its robustness, or under representative of the real trends in underlying populations.

Literature Review

Previous studies

There is some literature on the ICT divide between modern microelectronics. The first batch of studies explores the significant influence of intervening factors behind the different demand for phones and PCs in Africa. Some of these studies quantify regional determinants [Zhu et. al. (2006)], national factors [Pew Research Center (2015)] or international shocks [Yu et. al. (2010), Gartner (2009)]. Although these studies only focus on the ICT growth in developed countries or in both developed and developing regions [Fong (2009)], the underlying principles are nonetheless useful for my study in highlighting potential control variables.

Moreover, the next group of studies estimates the socioeconomic benefits arising from increased demand for phones. Attewell (2004) studies large-scale impacts of ICT diffusion whereas [Okazaki (2015), Sam (2017), Unwin (2007)] respectively investigate different micro levels. Okazaki (2015) finds that phones enhance consumer social participation. Additionally, Sam (2017) shows that phones promote socioeconomic growth while Unwin (2007) proves that phones improve labor training in Africa. These studies highlight the unexplored potential in phone use in Africa, and simultaneously reveal the competition between phones and PCs.

Another group of studies takes a different approach by strictly exploring the digital divide[5]. Studies such as Rouvinenc (2006) explore the persistent ICT divide between developed and developing regions, and between phone and PC use. Their findings favor phones as the key ICT instrument to shape the Internet and communications sectors in Africa. These conclusions are closest to my study interest, revealing that phones currently have a marked advantage over PCs considering the regional challenges common in Africa. Accordingly, my study also avoids reverse causality by explaining PC demand using phone demand and not the other way around.

Also, other studies analyze the potential for technological leapfrogging[6]. Vagliasindi (2006) represents studies that investigate the link between telephones and mobiles. They find that mobiles substitute rather than complement cumbersome fixed phones, cp[7]. This case reflects Africa, where abundant mobile use eclipse fixed phones. Since Africa has leapfrogged over fixed phone to mobiles, I combine the fixed and mobile phone demand in my study. Secondly, Soete (1985) investigates the link between ICT diffusion and technological leapfrogging in developed areas. The paper concludes that rapid productivity and competition in the 20th Century developed

[5] Inequality regarding access to, use of, or impact of ICT

[6] The notion that areas which have poorly-developed technology or economic bases can move themselves forward rapidly through the adoption of modern systems without going through intermediary steps

[7] Ceteris paribus

countries were prime conditions for technological upgrading. Africa ICT reflects those 20th Century ICT penetration rates but has access to modern upgrades. Consequently, rather than develop its own local ICT sector by trial and error, why not skip to the most advanced yet affordable technology? It has done so by relying on the mobile phone. These studies[8] also suggest, by extension, that African homes may forsake their PC demand for mobile use.

As it stands, my study is unique. As seen above, most studies analyze the causes of/impacts of ICT growth in Africa. Similarly, most methodologies hardly disaggregate ICT influence. Hence, there is no known literature that has directly analyzed the relationship between mobiles and PCs in Africa. My paper is the first to analyze the interactions in demand between different ICT components in 21st Century sub-Saharan Africa. My focus is motivated by Comin (2015). I suspect that the slowness in PC penetration in Africa is partially due to accelerated phone diffusion. As such, I disaggregate ICT influence to focus on the internal impact of phones on demand for PCs rather than the external impact of ICT on socioeconomics in Africa. This analysis can help re-specify ICT policies to strategically maximize ICT growth in Africa.

Basic Model

To investigate the relationship between phones and PCs, I use a model like Tavares (2015). I hypothesize that homes use mobiles as substitutes to PCs to overcome the numerous socioeconomic challenges that pertain to PCs e.g. enhanced insecurity, limited insurance and ICT infrastructure etc. Hence increased mobile demand should decrease PC demand. Meanwhile, firms use phones as complements to PCs since firms are better placed to overcome most socioeconomic challenges related to PC use. Moreover, firms are more reliant on diversified ICT services for profit making. Correspondingly, an uptake in phones should induce an uptake in

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[8] Though data on demand for phones and PCs date to the 1960s, most data and studies for Africa only pick up around post 2000

PCs. Since most of my controls are time invariant e.g. gender, my paper uses linear fixed effects (generalized in Equation 1) with $Phone_{ct}$ as the key regressor and PCs as the regressand:

Equation 1: $PC_{ct} = b + b_t + b_c + \delta_1 \, Phone_{ct} + \alpha_i X_{ct} + v_{ct}$

where X_{ct} is a vector of independent variables for each country-year unit, b is a constant, b_t and b_c are fixed effects, v_{ct} is the error term and c = Country 1,2 etc.

The dependent variable is PC_{ct}. This discrete variable tracks PC demand in various African nations across time. If the postulated δ_1 is positive, then PCs and phones are complements; if negative, then PCs and mobiles are substitutes. Similarly, the estimated coefficients on the control variables show the influence each variable has on PC demand. Meanwhile, phone use ($Phone_{ct}$) is the main explanatory variable. This discrete measure captures the average phone subscription for each country year unit.

X_{ct} contains country specific factors. These factors stem from prior studies explored in the literature review. These factors are also diverse and numerous, reflecting the serious concerns that plague the sub-Saharan Africa ICT sector but are less impactful in North Africa. These characteristics include measures for macro level aspects e.g. ICT and Internet infrastructure, democracy, openness, GDP and credit access. Additionally, the micro level components include literacy, geography, English speaking, employment, access to TV/radio and age. Of these variables, I expect a negative correlation when considering rural areas, mobile banking, internet costs, non-English speaking, female, unemployed, the old and no access to radio. The remaining control variables should have a positive correlation with PC_{ct}. Aside from these controls, year (b_t) and country fixed effects (b_c) are captured via indicator variables to prevent autocorrelation.

To back up my expectations, my paper runs robustness checks. These test for outliers, endogeneity and mis-specification.

Data Highlights

My paper tests whether phones are complements/substitutes to PCs in Africa[9]. My dependent variable, PC_{ct}, is explained under Literature Review. In addition, my paper uses the proportion of firms with websites as a proxy variable for firm PC demand because ICT firm data is limited. The main explanatory variable is $Phone_{ct}$. For home analysis, I use: *Mobile_100* which tracks mobile subscriptions per 100 inhabitants in a country c at year t. My study also uses *Phones_100* to track aggregate measures of both mobiles and telephones per 100 inhabitants in country c at year t. *Phones_100* assumes that some of the phone subscribers are direct firms. 'Phone' is also appropriate for firms since I could not find firm phone use data breakdowns.

My paper uses an unbalanced panel data of 369 observations from 2000-2011 for home analysis. On the other hand, the firm panel data of 68 observations from 2005-2015 is strongly balanced. My paper then re-specifies the data to run secondary analyses as well.

Data Description

Most of my data is from the WB and ITU. The key variables are discussed under Data Highlights. This section describes control variables[10]. Home control variables include *GDP_Cap* (GDP per capita in $), *Labor* tracks labor trends, *Urban_pop* tracks urban populations relative to total populations, and *Literacy* tracks literacy rates in inhabitants above 15 years old. Economic controls are *Openness* (trade relative to GDP), *Credit_access* (domestic credit relative to GDP), *Inter_Subs* (broadband subscribers per 100 inhabitants), *Inter_cost* (annual Internet costs) and [*Hhold_TV, Hhold_Radio*] showing respective media users per 100 inhabitants.

[9] Check Appendix Section 1 for statistics
[10] Check Appendix Section 2 for more details

Firm controls are slightly different. They include {*Ltd_Partnership, Partnership, Private, Public*} defining percentage of surveyed firms with respective listings. *Firmage* tracks the establishment's age in years. Electrical controls are *Elect_Delay* (days to acquire electrical connection post application), *Outage_Time* (outage durations in hours), *Outageloss* (losses relative to annual sales) and *Gen_elec* (proportion of electrical supply from a generator). *Collateral* then tracks collateral needed for loans (%) while *Efficiency* is capacity utilization (%). Lastly, I incorporate some demographic controls such as {GDP*_Cap, Labor, Urban_pop, Literacy, Openness, Inter_Subs and Inter_Cost*} as they influence business contexts too. Other controls are secondary. For instance, I create a mobile banking variable control.

A preliminary run of these controls shows that they have outliers and are left skewed. I correct these issues by dropping outliers and transforming some of these controls to log forms.

Data Analysis

Empirical design

My empirical implementation sorts WB data into time varying and time invariant variables[11]. To investigate my research question at home level, I combine WB time varying variables with ITU data. Thus, relevant control variables track time varying elements e.g. GDP, traditional media, labor, credit access, openness, literacy and urbanization. The analysis runs 48 countries per year.

My key variable of interest is $Mobile\_100_{ct}$. My paper estimates OLS equation 4:

Equation 4: $HholdPC\_percent_{ct} = b + b_t + b_c + \delta_1\, Mobile\_100_{ct} + \alpha_1\, Hhold\_TV_{ct} + \alpha_2\, Hhold\_Radio_{ct} + \alpha_3\, lInter\_Cost_{ct} + \alpha_4\, lInter\_subs_{ct} + \alpha_5\, Credit\_access_{ct} + \alpha_6\, Openness_{ct} + \alpha_7\, Literacy_{ct} + \alpha_8\, Urban\_pop_{ct} + \alpha_9\, lLabor_{ct} + \alpha_{10}\, lGDP\_Cap_{ct} + v_{ct}$

[11] Check Appendix Section 3 for more details

All the variables are in percentage or natural log forms for easy comparison. The control variables are included to isolate the causal relationship of interest(δ_1). The fixed effects are captured via indicator variables for year and country to reduce bias. Moreover, my study also runs a fixed effects equation 5 and a random effects equation 6 using these variables. Equations 5 and 6 are compared via Hausman tests to determine which model is better suited for my study.

My paper then replicates this method for firm analysis. Once more, I combine time varying WB data with ITU data. The control variables track firm age, GDP, openness, labor, Internet, literacy, urbanization and firm specific elements including efficiency, collateral, electricity, and type of firm. This analysis also uses 48 countries per year.

My key variable of interest is $Phones\_100_{ict}$ as shown in OLS equation 7:

Equation 7: $PC\_Demand_{ict} = b + b_t + b_c + \delta_1 Phones\_100_{ict} + \alpha_1 Firmage_{ict} + \alpha_2 Firmage^2_{ict} + \alpha_3 lInter\_Cost_{ict} + \alpha_4 lInter\_Subs_{ict} + \alpha_5 Efficiency_{ict} + \alpha_6 Openness_{ict} + \alpha_7 Literacy_{ict} + \alpha_8 Urban\_pop_{ict} + \alpha_9 lLabor_{ict} + \alpha_{10} lGDP\_Cap_{ict} + \alpha_{11} Collateral_{ict} + \alpha_{12} Gen\_elec_{ict} + \alpha_{13} Outage\_Time_{ict} + \alpha_{14} Outageloss_{ict} + \alpha_{15} Elect\_Delay_{ict} + \alpha_{16} Ltd\_Partnership_{ict} + \alpha_{17} Partnership_{ict} + \alpha_{18} Private_{ict} + \alpha_{19} Public_{ict} + v_{ict}$

All variables are expressed in percentage or log forms. The control variables isolate the potentially causal relationship of concern(δ_1). The fixed effects are captured via indicator variables for year and country to reduce bias. $Firmage^2$ captures the non-linear age effect. Again, my paper runs equation 8 and 9 using these same variables for Hausman comparison.

<u>Results</u>

The main statistical results[12] of my study are shown in tables 2 and 3. Table 2 presents the home estimates while table 3 presents the firm coefficients. Table 2 shows output from equations 4, 5 and 6 [include year and country fixed effects]. Columns 4 and 5 run equations 5

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[12] Check Appendix Section 4 for statistical output

and 6 respectively. Generally, the specifications strongly explain the data, having $R^2 > 65\%$. I also reject the F test null hypothesis that slope coefficients are jointly equal to zero at any level of confidence. However, since Hausman test null is rejected, my study uses the fixed effects estimation (Column 4) for consistent estimates. In column 4, the coefficients of *Hhold_Radio* and *lInter_subs* are positive while the estimates of *Household_TV_Proportions* and *lLabor* are negative; qualitatively mirroring what some researchers like Yonazi et. al. (2012) have estimated. These findings are largely consistent with ICT theory suggesting that internet and radio access have positive impacts on PC demand whereas TV access reduces PC demand, all things equal.

My major concern in this section is the relationship between mobiles and PCs in sub-Saharan Africa. In column 2 and 4 of table 2, the estimate of *Mobile_100* is strongly positively significant, suggesting a positive relationship underlying mobiles and PCs for African homes. Effectively, an increase of 1%-point in mobiles per 100 inhabitants is correlated with a rise of .05 %-points in PCs per 100 inhabitants, cp. This estimate is economically viable; implying that promoting local mobile access yields some observable positive externalities in computer access in Africa. Nonetheless, this estimate contradicts my hypothesis. I attribute this outcome to various factors. Since my sample is limited in size after dropping missing data, this estimated coefficient may be biased downwards in magnitude. Nonetheless, this outcome holds true for my sample. Since this positive relationship between mobiles and PC demand persists across different specifications, this suggests that the observed mobile-PC link may have modest policy potential.

In column 4 of table 2, the estimate on *lInter_subs* is significant at = .05. This positive influence is expected as internet services normally work best on PCs. Consequently, increased internet networks correlate with increased PC demand, cp. In addition, *Hhold_Radio* positively correlates with PC demand. Specifically, an increase of 1%-point radio use per 100 inhabitants induces a rise of .01% points PCs, cp. This outcome is unsurprising because radios offer ICT exposure but are limited in use, which is overcome via versatile PCs.

On the other hand, the coefficient of *lLabor* is negative and significant at=.05, indicating a negative relationship between PC demand and labor. This outcome is baffling. I postulate that this perplexity may arise labor intensive countries are simultaneously capital deficient. If so, most homes may be labor intensive but low skilled thus demanding low paying jobs that exclude wealth for PC demand. However, this estimate is grossly large, implying a high possibility that this estimate is mis-specified or biased. As such, I place little emphasis on this outcome.

Additionally, the coefficient on *Hhold_TV* is strongly negative. An increase of 1%-point in TVs per 100 inhabitants is correlated with a decreased PC demand of .05%-point, cp. I had no prior expectation on this unit. I surmise this outcome as possible if TVs provide some entertainment value otherwise associated with PCs, thus less need for PCs in homes. Since radio and TV have equal but opposite effects on PC demand, this suggests that there may be more to unearth in the ICT interactions in future studies.

Next is firm level analysis in table 3 which shows output from equations 7,8 and 9. Equation 7 includes year fixed effects, 9 has country fixed effects and equation 8 lacks year and country fixed effects due to sample size. Column 2 shows equation 7's output while columns 4 and 5 represent equations 8 and 9 respectively. My specifications strongly explain the data, having $R^2 \geq 75\%$. The Hausman test confirms that data is homoscedastic. Since xtreg estimates are independent, I use the fixed effects model for consistency with previous analysis (Column 4). In column 4, several coefficients are strongly significant e.g. *lInter_Cost, Urban_pop, Efficiency, Gen_elec* and *Openness* are positive while *lInter_Subs, Collateral* and *Literacy* are negative. These findings show that firm and demographic factors can significantly impact firm PC demand.

My main regressor, *Phones_100*, has a statistically positive estimate. A 1%-point rise in phones per 100 inhabitants yields a rise in PC demand of .01%-points, cp. The sign on this estimate is as expected in my hypothesis, confirming that access to phones within sub-Saharan African firms also stimulates industrial PC demand. However, the estimate is smaller than anticipated hence economically limited in usefulness. I explain this magnitude using previously mentioned data concerns. Even so, this estimate may significantly increase with larger samples. All in all, this estimate persists across varied specifications shown in columns 2-5, suggesting that the observed phone-firm PC link is also possibly useful in policies.

In column 4, the estimate of *lInter_Cost* is significant at = .01, suggesting a strong positive relationship between PC demand and internet costs. This outcome is unexpected as internet costs usually impede PC use. This estimate is likely wrongly specified hence I do not place much emphasis on it. *Urban_pop* also shows a stronger significant influence on PC demand. This is unsurprising since urbanization involves closer and more frequent access to ICT exposure. What is more, firm specific attributes such as *Gen_elec* show positive effect on PC demand. This is expected given that superior firms are also well placed to exploit the diverse advantages of PCs, and generator supply stabilizes energy supply enabling more PC investments to capitalize on the energy infrastructure. Consequently, increased firm effectiveness increases PC demand.

Efficiency and *Openness* are the strongest positive influencers of PC demand at firm level. Efficiency estimates that a rise of 1%-point in capacity utilization corresponds to a rise of .6%-point PCs, cp. Also, openness shows that a 1%-point increase of trade as a percentage of GDP induces a strong rise of 1.14 %-point demand of PCs, cp. These estimates are not surprising as far as the correlation goes, since economic symmetry usually spurs ICT growth.

On the other hand, *Collateral* negatively impacts PC demand. This is expected since firms rely on liquidity for performance. Anything that ties up capital e.g. unnecessary PCs, threatens firm success. But, *literacy* and *lInter_Subs* are unexpectedly negatively correlated with PCs. Specifically, a 1%-point boost in internet subscriptions yields a decline of 14.94%-points in PCs, cp. Since the estimate is very large and the regressand is very small and variable, this number is likely over magnified too. Thus, I place minimal emphasis on it. Perhaps this outcome may occur if firms utilize the existing internet access within the labor force, minimizing further PC demand.

Further analyzing the firm data reveals a few trends. First, an age effect: represented by the statistically positive effect of *Firmage* and paired with the statistically negative influence of *Firmage2*. This pair shows that older firms demand more PCs but at a declining rate. In my output, a 1 year increase for the firm correlates with a rise of 11.67%-points in PC demand at a declining rate of .34%-points, cp. This age effect is large but not surprising in sign as commonly shown in many econometric studies.

Another interesting effect is the outage effect. This is shown in column 4 of table 2 by a statistical decrease in PC demand via *Outageloss* and *Outageduration*. The final effect likely combines both elements. *Outageloss* is the stronger component, estimating that an increase of 1%-point in outage loss yields a cp decline of 6.3%-points in PC demand. This is expected because firms strategize their ICT investments in such a way to minimize risk exposure. Since losses hurt firm profitability, affected businesses are less likely to demand PCs which are highly susceptible to outage shocks if electricity supply is uncertain. This result suggests that as outages continue to plague Africa, the demand for PCs may continue to show lackluster growth.

The third firm effect explores the differences between different types of firms, especially *Ltd_Partnership*, *Partnership* and *Public*. Their estimates are statistically significant and positive at=.05 or above. *Public* is the relatively strongest effect and suggests that every 1% -point increase in public firms corresponds to a rise of 1.66%-points in PC demand compared to sole proprietorships, cp. Such legal disparities possibly stem from the relatively greater role of PCs in these firm types e.g. public firms are larger and more PC intensive than sole proprietorships.

These results have some research and economic implications. Given the modest relationship between phone use and PC demand that I find, researchers can do more in using mobile use (related aspects) as a regressor in investigating ICT dynamics in African homes and industries. This is especially vital to prevent wrongly specified ICT growth equations. Moreover, my topic did not cover the mechanisms behind the influence of phones on PCs. This is an area for further study. From a policy standpoint, my results suggest that policy makers should make reasonable efforts to improve phone infrastructure to boost related ICT growth in homes. Since reducing outages could spur ICT industrial development, researchers should also explore stronger models to highlight the precise influence of electrical infrastructure on firm PC demand. Policy makers should also promote initiatives on ICT interconnections and industrial support since highly productive firms may generate positive externalities for the residents.

Robustness Checks

To test the robustness of my results, I run sensitivity checks on the coefficients of phone/mobile demand, my main variables of interest[13]. My robustness checks are broadly classified into three categories: outlier checks, endogeneity checks and specification tests.

My first outlier test[14] identified outliers in various variables. After re-estimation, the effect is positive as my data shows less variance and plots are within expected range, as shown in

[13] Check Appendix Section 5 for more details; Tables only report coefficients- no standard errors
[14] The *sum* function

Appendix Section 2. Additionally, because my ICT data is duplicated in the WB and ITU datasets, I conduct another robustness check by comparing the key variables of interest: *Household_PC_Proportions* from WB against *HholdPC_percent* from ITU; and *Mobile_100* against *Mobile_x* from WB. Various comparisons reveal that the ITU estimates are more data superior. Consequently, my paper uses ITU data for key variables and WB for controls. Furthermore, I collect telephone data from WB but it has missing data. Thus, my study uses mobiles for households and phones for firms. Another concern is the possible skewness from larger regions in my sample. To test for this concern, I exclude East Africa as a sample region (due to its relative accessibility to most of ICT trade from international markets). The overall estimate loses statistical significance as shown in table 5, suggesting that my sample may contain regional influence. Consequently, I include caveats on the generalization of my findings. My next robustness section tests endogeneity. Running White test to identify potential heteroscedasticity shows output in table 6. This reveals heteroscedasticity in my data which I minimize using robust standard errors and by transforming variables to logs and percentages.

My third robustness type tests consistency of estimates across different specifications. First, I run a time-based selection. I replicate equations 4,5 and 6 using post 2008 data to allow for sufficient penetration of ICT into African economies. The regression effects are seen in columns 3 of table 2 and 3. The estimate on *Mobile_100* loses statistical while other estimates hold steady, suggesting that my sample shows some temporal robustness. My next specification analyzes whether PC/mobile demand is emphasized in laborers who are employed by ICT operators, presumably since these laborers have superior knowledge of ICT. As seen in table 7, the estimates of interest on *Mobile_100* and *Phones_100* persist in sign and have minimal change in magnitude while *lphonelabor* shows no statistical significance, implying that there is no observable

ICT sample selection bias. Another specification only tests African countries with the strongest data availability. As seen in table 8, the estimate of interest loses statistical significance, suggesting potential unobserved bias in my sample due to limited data. Finally, I run a specification to isolate the potential effect of mobile banking, which presumably negatively affects PC demand. Using WB data, I include an aggregated mobile banking index for available countries. Nonetheless, as seen in column 2 of table 9, the estimate on *Mobile_Banking* is not statistically significant. This measure is possibly underestimated because of limited data. As seen, my robustness checks yield promising results but suggest there is room for improvement.

Conclusion

This paper uses panel data from sub-Saharan African countries over the 2000-2015 (for homes) and 2005-2015 (for firms). My paper uses restructured panel data estimations to investigate the effect of mobile/phone use on PC demand, and investigates some of the subtle dynamics related to phone use. Using xtreg equations, I find that phone use has a positive and significant impact on PC demand in both sub-Saharan African homes and firms. I also find that openness, Internet, electricity and some ICT media have strong impacts on the demand for PCs. Finally, I conclude that phones and PCs are moderate complements in sub-Saharan African homes and weak complements in sub-Saharan African firms. This confirms half of my initial hypothesis. My results are robust to different specifications but can be improved on with bigger samples. Lastly, my results have both research and policy implications for African economies.

- ***Appendix & Work Cited Excluded***