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ABSTRACT

Broadband Internet and Household Welfare in Senegal*

Senegal has experienced a rapid expansion in fixed and mobile broadband Internet infrastructure over the past decade. This paper examines the relationship between access to broadband internet and household welfare between 2011 and 2018 by integrating the latest two rounds of household budget surveys with data on the location of fiber-optic transmission nodes and coverage maps of third-generation (3G) mobile technology. Results show that 3G coverage is associated with a 14 percent increase in total consumption and a 10 percent decline in extreme poverty. These results are robust to controlling for spatial characteristics and access to complementary digital infrastructure, as well as to an instrumental variable approach that relies on distance to 3G coverage in neighboring areas. These effects are larger among households in urban areas and households headed by men or younger cohorts. Although in the same direction, welfare effects of proximity to fixed broadband infrastructure are not statistically significant.

JEL Classification: F63, I31, L86, O12

Keywords: poverty, household consumption, mobile broadband, Africa, Senegal

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1. Introduction

As the use of digital technologies expands in Sub-Saharan Africa, it is becoming more important to understand the effects of these technologies on welfare. The adoption of digital technologies—defined as "the Internet, mobile phones, and all the other tools to collect, store, analyze, and share information digitally" (World Bank 2016)—can potentially translate into economic opportunities among large numbers of people in the region. A small, but rapidly growing body of literature documents the positive impacts of Internet access on various outcomes of interest. Cross-national studies show, for instance, a positive relationship between economic development and the expansion of digital technologies in the form of increases in fixed broadband penetration rates (Czernich et al. 2011; García Zaballos and López-Rivas 2012; Qiang and Rossotto 2009). Studies also show that access to cellphone coverage improves employment, as well as welfare in terms of greater consumption and a reduction of poverty (Blumenstock et al. 2020; Klonner and Nolen 2010).

Most studies, however, focus almost exclusively on cellphone access, that is, second-generation (2G) technologies, and limited research on fixed broadband Internet.[1] Little is known about the effects of mobile broadband Internet—for instance, third-generation (3G) and fourth-generation (4G) technologies—on the welfare of individuals and households. This distinction is particularly important in the context of African countries, where a majority of people access the Internet through mobile phones rather than through fixed broadband Internet.[2] Recent evidence thus suggests that an expansion of fixed broadband Internet would enable more rapid job creation, more economic activity in Africa, and greater productivity and export growth among firms (Hjort and Poulsen 2019). New research also shows that the rollout of mobile broadband Internet has increased household consumption and reduced moderate and extreme poverty in Nigeria (Bahia et al. 2020).

This paper builds on the nascent literature on the welfare effects of mobile Internet in developing countries, and, in contrast to previous studies, it sheds light on the welfare impacts of both fixed and mobile broadband Internet coverage. Senegal has experienced a more rapid expansion in digital technologies over the past decade relative its peers, such as Côte d'Ivoire, Kenya, and Rwanda. A growing share of Senegalese have gained access to cellphone services and mobile and fixed broadband Internet. A recent report suggests that 98.7 percent of users access the Internet through mobile phones, emphasizing the importance of mobile broadband Internet in the country (ARTP 2019).

The study exploits the two most recent household budget surveys undertaken in Senegal: the 2011 Deuxième Enquête de Suivi de la Pauvreté au Sénégal (Second Poverty Monitoring Survey, ESPS-II) and the 2017–18 Enquête Légère Expérimentale sur la Pauvreté (2017–18 Light Experimental Poverty Assessment Survey, ELEPS). It integrates the data of these surveys with data on the expansion of mobile broadband coverage and fiber-optic network infrastructure to examine how the coverage of and proximity to digital infrastructure may influence household consumption and poverty status. It matches the locations of households—based on GPS coordinates of census enumeration areas (EAs, the primary sampling units)—with maps of terrestrial backbone networks and 2G and 3G coverage

[1] 2G technologies enable voice, SMS, and limited Internet access, while third-generation (3G) technologies enable more rapid Internet browsing and data downloading.

[2] The number of active mobile broadband subscriptions per 100 inhabitants in Africa in 2017 was 34.0, while the corresponding rate for fixed broadband subscriptions was 0.4 (ITU 2019).

maps.[3] As discussed more extensively by Hjort and Poulsen (2019), the proximity of a given location to a terrestrial backbone network affects the Internet speed available at the location. The provision of 3G or 4G coverage also enables access to high-speed Internet through mobile phones, while 2G coverage only provides for limited Internet browsing and applications.

The analysis concludes that mobile broadband coverage is associated with greater household consumption and with reduced poverty status. These relationships are robust after the study controlled for household demographics and other spatial characteristics, as well as for access to other, complementary digital infrastructure such as 2G coverage or fixed broadband Internet. The welfare effects, however, do not appear to be uniform across subgroups. The positive welfare effects of 3G coverage are more evident for households in urban areas or headed by men or younger cohorts. In addition, although there is a positive correlation between proximity to fixed broadband infrastructure and welfare, this relationship becomes insignificant after one controls for other geographical characteristics, such as region fixed effects, road density, nighttime lights, or elevation above sea level.

This paper makes two distinct contributions to the literature. First, it is among the first papers to measure the effects of mobile broadband and fixed broadband infrastructure on household welfare. Most studies focus on cellphone (2G) access, while much less is known about the welfare impact of fixed or mobile broadband Internet. The studies that do look at the Internet tend to focus on fixed broadband rather than mobile broadband Internet (Hjort and Poulsen 2019).[4] This distinction is important because mobile broadband Internet is the main technology used to access the Internet in Senegal. By considering both technologies, the study sheds light on the infrastructure gap and the complementarities that exist between the technologies.

Second, this appears to be the only paper that relies exclusively on the rich data available from household consumption surveys to measure the welfare implications of various types of digital technologies, that is, mobile phone access, fixed broadband Internet, and mobile broadband Internet.

The analysis applies a robust methodology that can be used to assess the impact of mobile and fixed broadband Internet across Sub-Saharan Africa as more data on coverage and connectivity become available. In addition, the results contribute an important perspective to the policy discussion on the degree to which digital infrastructure can serve as a welfare- and resilience-enhancing mechanism. By demonstrating that broadband coverage can improve consumer welfare and reduce poverty, the paper supplies evidence on the positive spillovers of connectivity. This empirical evidence can be useful to policy makers in addressing public investment gaps across various sectors of infrastructure.

The rest of the paper is structured as follows. Section 2 describes the data sources, while section 3 presents the estimation strategy. Section 4 discusses the results, and section 5 concludes.

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[3] Data on backbone networks have been taken from Africa Bandwidth Maps (database), Hamilton Research, Bath, UK, http://www.africabandwidthmaps.com/. Internet traffic in countries runs first through national backbone or fiber-optic networks, which are then connected to end users through last-mile infrastructure, such as fiber cables, copper cables, wireless transmission, or cellphone towers. 2G, 3G, and 4G mobile coverage maps have been obtained from three major telephone communication providers—Orange (or the local subsidiary Sonatel), Senegal Expresso, and Tigo—and Mobile Coverage Maps (database), Collins Bartholomew, HarperCollins Publishers, Glasgow, https://www.collinsbartholomew.com/mobile-coverage-maps/.

[4] Bahia et al. (2020) are a notable exception. They explicitly test the impact of 3G and 4G technologies on consumption and poverty using data on Nigeria.

2. Data

Senegal represents a valuable case study. The rise in the number of cellphone users and Internet subscribers in the country over the past decade has been significant compared with peer countries. Figure 1 illustrates the both mobile cellular subscriptions and fixed broadband subscriptions in Senegal relative to peers—Côte d'Ivoire, Kenya, and Rwanda—as well as among the 5th and 95th percentiles overall in Sub-Saharan Africa.

[Figure 1]

The data on consumption and poverty are derived from official household budget surveys: the 2011 ESPS-II and the 2017–18 ELEPS. The 2011 ESPS was a nationally representative survey that was fielded between August and November 2011. It was conducted effectively with 17,891 of the 18,180 households sampled given that the response rate was 98.4 percent. About a third of these households were interviewed using the entire household questionnaire on expenditure. The 2017–18 ELEPS is comparable with the 2011 survey. The ESPS was administered among 1,065 of the 1,200 households sampled given that the response rate was 89 percent. The sample was spread across the country according to three geographic areas: Dakar, other urban centers, and rural areas.

To measure access to fixed broadband Internet services across Senegal, the analysis relied on information on the locations of fiber-optic transmission nodes that was obtained from the Africa Bandwidth Maps database.[5] The analysis considers how distance to operational fiber-optic nodes may influence welfare and poverty across the country. Map 1, panel a, shows the locations of fiber-optic transmission nodes in Senegal. These nodes correspond to add or drop points (entrance or exit) in the long-haul fiber networks. It is useful to think of long-haul fiber networks as motorways that have junctions (on and off ramps that is, add and drop points) that feed smaller class roads (access fiber, wireline, and wireless networks). In the motorway scenario, even if a household is located close to the motorway, it may be a long drive to the nearest junction. The same applies to fiber-optic networks, in which the speed of fixed broadband Internet is determined by proximity to the transmission nodes rather than the network lines connecting the nodes. The transmission nodes are categorized by operational status: operational, under construction, and planned or proposed.

[Map 1]

Mobile coverage data are drawn from two sources: the Mobile Coverage Maps database and mobile operators in the country. Data on mobile phone coverage and mobile broadband Internet coverage compiled in the Mobile Coverage Maps database by Collins Bartholomew are based on voluntary submissions made directly by mobile operators for the purposes of constructing roaming coverage maps for end users. The temporal coverage of the data varies depending on 2G and 3G coverage, respectively, in 2011–17 and 2014–17.[6]

To ensure that the findings are not an artifact of potential missing information in the Mobile Coverage Maps database, the analysis also utilizes 2G and 3G coverage information collected directly from the

[5] See Africa Bandwidth Maps (database), Hamilton Research, Bath, UK, http://www.africabandwidthmaps.com/.
[6] The Mobile Coverage Maps database contains no information on 4G coverage. Moreover, the coverage maps depend on information shared voluntarily by mobile operators. So, their quality should be checked for completeness against other sources of data. For this, the analysis here relies on data collected directly from major mobile operators.

three major mobile operators in Senegal: Expresso, Orange (or its local subsidiary Sonatel), and Tigo. While the coverage maps obtained from Expresso and Tigo are limited to 2016, Orange's coverage maps are available for 2016–18. Orange-Sonatel dominates the fixed and mobile markets, dwarfing the market shares of other major providers, such as Expresso (22 percent) and Tigo (24 percent) (BuddeComm. 2020). Orange is also the first provider of 4G technologies in Senegal (Oduor 2016).

The data newly collected from providers show a much wider coverage of 3G technologies in Senegal than otherwise suggested by the Mobile Coverage Maps database. For instance, the median distance between the centroids of EAs in the 2017–18 ELEPS and the closest coverage areas of 3G technologies was 1.8 kilometers based on the Mobile Coverage Maps database (see map 1, panel b). Yet, the distance was only 0.4 kilometers based on the data provided by Orange-Sonatel for the same year (see map 1, panel c). There is thus a substantial discrepancy in mobile coverage data across the various sources of information. The analysis therefore combines the data from all the various sources of information to ensure that the 3G coverage maps are as complete as possible.

The analysis also uses the GPS coordinates of the centroids of EAs to match the locations of the households in the survey data and the fiber-optic nodes and mobile coverage maps. It would have been ideal if the exact locations of households were merged with spatial data on digital technologies. Nonetheless, the GPS coordinates of the centroids of EAs are the best source of geographical referencing data available for identifying the location of households. The same approach is adopted by Hjort and Poulsen (2019), who demonstrate that the distance between the terrestrial backbone infrastructure and sampling cluster locations still provides a reasonable measure of the accessibility to the Internet.

3. Estimation strategy

To estimate the impact of fixed and mobile broadband Internet on household outcomes, the following equation is calculated:

$$y_{irt} = \alpha + \beta_1 DT_{irt-1} + \boldsymbol{\gamma}\mathbf{X}_{irt} + \theta_r + \tau_t + \varepsilon_{irt}, \qquad (1)$$

where y_{irt} is the outcome of interest, that is, the consumption or poverty status of household *i* in region *r* at year *t*. In addition to total consumption, food and nonfood consumption are also separately considered. These consumption variables are all log-transformed because of the large skewness and kurtosis values. The poverty status of households is determined by the international extreme poverty line of $1.90 per day or low-middle income international poverty line of $3.20 per day.[7] To account for any potential bias arising from the sampling, we apply probability weights for our main results.[8] The use of sampling weights renders our estimates nationally representative.

DT_{irt-1} denotes access to fixed and mobile broadband Internet proxied by connectivity to the fiber-optic network and 3G coverage, respectively. Connectivity to fixed broadband Internet is operationalized through a binary variable that takes a value of 1 if the household lives in an EA the centroid location of which is less than 1 kilometer from the closest functional fiber-optic node for

[7] https://blogs.worldbank.org/developmenttalk/richer-array-international-poverty-lines.

[8] It is worth noting that our main analytical conclusions remain consistent regardless of whether sampling weights are applied in our regression. See Annex for details.

fixed broadband Internet.[9] For mobile broadband Internet, the treatment is coded 1 if a given household lives in an EA in which the centroid is covered by 3G technologies.[10] The treatment variables are lagged one year because it is most likely that there is some temporal lag between the arrival of digital infrastructure (e.g., fiber-optic nodes or 3G) and the manifestation (if any) of the welfare effect.[11] Because the first round of the 2011 survey does not reveal information on 3G mobile coverage, the welfare effect of 3G coverage can be tested only using the 2017–18 ELEPS. The analysis of the 4G network is not considered extensively in the main analysis of this paper because Senegal had not yet deployed a full 4G network in 2018, the year the latest household survey was collected. Indeed, 4G was only introduced in Senegal in 2016, and 4G coverage remains limited to a few urban centers of the country.[12]

The set of control variables X_{irt} includes household size, the marital status and sex of household heads, access to electricity, literacy of household heads, housing conditions (as measured in a composite index of dwelling characteristics[13]), and a group of EA-level variables, including nighttime lights, road density, and elevation above sea level.[14] In addition, θ_r and τ_t are region fixed effects and year fixed effects. Controlling for other types of infrastructure, such as road connectivity or electricity, is important given that, in most African countries, "a part of the backbone network runs parallel to other infrastructure such as roads or electricity cables" (Hjort and Poulsen 2019, 1053). Descriptive statistics on key outcome variables, treatment, and other covariates and controls are reported in table 1.

[Table 1]

The main object of interest is coefficient β_1, which captures the effect of access to digital infrastructure on welfare and poverty. To account for the existence of heteroskedasticity and serial correlation, standard errors are clustered according to the relevant EAs.

To identify β_1, the analysis assumes no endogeneity or $\mathrm{E}[\varepsilon_{irt}|DT_{irt-1}, \mathbf{X}_{irt}, \theta_r, \tau_t] = 0$. This assumption is violated if there are any unobservable, omitted variables that confound the relationship

[9] The findings do not change if the distance threshold of 1 kilometer is shifted to other distances (see appendix A).

[10] The Mobile Coverage Maps database 3G coverage maps are provided as polygon shapefiles, while some of the 3G coverage maps shared by operators are available only as point shapefiles. In the case of the point shapefiles, households were coded as covered if they were in EAs in which the centroids were less than 1 kilometer from the closest coverage points.

[11] As a robustness check, the contemporaneous effects of distribution terminals on consumption and poverty are also tested. The conclusions do not change whether the treatment is lagged or not (see appendix A, table A.2).

[12] See Pop et al. (2018) for more detail. Although 4G is beyond the scope of this paper, 4G coverage maps received from Orange-Sonatel (for December 2017 and December 2018) are used to test the impact of 4G technologies on consumption and poverty. The results are reported in appendix A, Table A.7. The finding is that 4G coverage is positively correlated with consumption and negatively with poverty, but this relationship is not robust to the inclusion of demographic and geographical controls.

[13] This wealth index is based on whether the household has the following: durable walls; durable roof; durable floors; access to toilet; access to water toilet; and electric or gas cooking fuel. Based on household responses to these questions, the index was calculated using a weighted-average, with weights derived from principal component analysis. The index is used because including the different components as separate variables introduces multicollinearity in the regression.

[14] Data on nighttime light, road density, and elevation are derived from NASA VIIRS (Visible Infrared Radiometer Suite), Meijer et al. (2018), and SRTM 90m DEM Digital Elevation Database, respectively. Positive expenditure on electricity bills is taken as a measure of access to electricity in both rounds of the survey because there is no other direct measure of household electricity access.

between the outcome of interest and the treatment. It is plausible, for instance, that places covered by 3G also tend to have local business environments that are more friendly to firm entry and job creation, which could, in turn, result in improvements in welfare. In this case, it would be incorrect to attribute improvements in welfare to 3G coverage alone.

To alleviate concerns about endogeneity, two-stage least squares regression analysis is employed as a robustness check. The distance to 3G coverage in neighboring areas outside the immediate vicinity of a given EA is used as an instrument for 3G coverage in the same EA. More specifically, an index of distance to 3G coverage is constructed that is defined as the weighted sum of the distance to 3G coverage in areas that are close to (within a 100-kilometer radius), but not within the immediate vicinity (within a 15 kilometer radius) of a given EA. Formally, this index is defined as follows:

$$3G\ Distance\ Index_{\,j} = \sum_{k=1}^{n} d_k\, w_{jk} / \sum_{k=1}^{n} w_{jk}, \qquad (2)$$

where d_k is the distance between location *k* and the closest 3G coverage areas, and w_{jk} is defined as the inverse of the distance between EA *j* and location *k*. Location *k* corresponds to the centroid of 0.0833 × 0.0833 degree (~10 × 10 km at equator) grid-cell $k = \{1,\ldots,n\}$ defined on the national boundaries of Senegal. For this calculation, only those locations are considered that are within a 15 kilometer –100 kilometer radius of enumeration *j*.

The instruments are valid if they meet two requirements: excludability and relevance. First, the instruments are excludable if they are conditionally independent from the error term in equation 1. There is little reason to believe that factors directly influencing the welfare of households in EA *j* also affect the distance to 3G coverage in neighboring areas outside EA *j*. Second, instruments need to be relevant or closely correlated with the endogenous variable. Connective digital infrastructure, such as cellphone towers, tend to cluster geographically, driven by market demands that are also spatially concentrated. Thus, distance to 3G coverage in neighboring areas is likely to impact the probability that households are covered by 3G in EA *j*, thus meeting the requirement of relevancy.[15]

4. Results

The main results are reported in table 2, which illustrates that 3G coverage is associated with higher household consumption. A positive correlation is also found between consumption and connectivity to fiber-optic nodes (significant at the 0.10 level), but the estimated effect is not significant after one controls for demographic and geographical characteristics. The estimated welfare impact of 3G coverage is robust across various model specifications with and without the additional set of demographic and geographical control variables. The total consumption among households covered by 3G technology is about 14 percent greater than the total consumption of households not covered by 3G.[16] In particular, nonfood consumption is significantly positively correlated with 3G coverage. The average nonfood consumption of households with 3G coverage is about 26 percent greater than the average nonfood consumption of households without 3G coverage.

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[15] The intuition is similar to that of Acemoglu et al. (2019), who use waves of democratization in neighboring countries or countries in the same region as an instrument for democratization in a country surrounded by those countries.

[16] Since our dependent variables are all log-transformed for consumption, we exponentiate the coefficients, subtract one from these numbers, and multiply by 100 to obtain a more precise, substantive interpretation of those coefficients. For instance, the coefficient for 3G coverage on total consumption (Column 2 in Table 2) is 0.134. This means for one unit increase in 3G coverage, total consumption is expected to increase by 14 percent, which is derived from exp(0.134)≈1.143 minus 1.

[Table 2]

The results suggest that 3G coverage is also associated with lower extreme poverty (based on the international poverty line of $1.9 per day). The estimated effects of 3G coverage on poverty are negative and statistically significant, both with and without the additional set of demographic and geographical controls (Columns 7 and 8 in Table 2). Notably, households covered by 3G exhibit an extreme poverty rate lower by about 10 percent relative to households without 3G coverage. [17] While 3G coverage is also correlated negatively with moderate poverty (based on the international poverty line of $3.2 per day), its effect is not robust to the inclusion of the additional set of controls (Columns 9 and 10 in Table 2).

It is plausible that the relationship between 3G coverage and welfare is being confounded by other factors. For instance, 3G coverage is likely correlated with the fiber network and with 2G cellular services, which are also likely to impact welfare directly. The estimated effects of 3G as reported in table 2 may thus be picking up the effects of fixed broadband Internet and mobile phone access together. Failure to control for these potential confounders could lead an overstatement of the relationship between 3G and welfare. As a robustness check, the same models as presented in table 2 are run, but with controls for connectivity to the fiber-optic network (or within 1 kilometer of the nearest fiber-optic transmission node) and controls for 2G coverage.[18] The main findings do not change (see appendix A, Table A.3). Furthermore, the main results are also robust to specifications including self-reported ownership of cellphone or Internet access as additional controls (see appendix A, Table A.4).[19]

One may control for various demographic and geographical factors, but miss other, unobservable confounders that bias the estimates. To alleviate the issue of endogeneity, an instrumental variable approach is applied. The results of the two-stage least squares regressions are reported in table 3. The first-stage regression shows that the instrument is strongly and negatively correlated with 3G coverage (see appendix A, Table A.1). This makes sense given that the likelihood that households in a given EA are covered by 3G is expected to decline if the neighboring areas are distant from the closest 3G coverage areas. The two-stage least squares estimates show results that are similar to the results of the ordinary least squares regressions; the effects of 3G on total consumption are positive and statistically significant, and these effects are particularly pronounced in the case of nonfood consumption. As expected, the effects of 3G on poverty are also negative and statistically significant (though at the 0.10 level) in the two-stage least squares regressions.

[Table 3]

[17] The point estimates do not change substantially if no weights are applied. According to our unweighted regressions, 3G coverage is associated with a 18 percent increase in total consumption and a 7 percent decrease in extreme poverty rate (see Table A.3 and A.4 in Annex). To put this in context, similar work for Nigeria—integrating household panel data and historical coverage maps—finds an 11.1 percent increase in total consumption and a 7.9 percentage point decline in extreme poverty after three years of coverage (Bahia et al. 2020). Using data from 14 rural and geographically isolated areas in the Philippines between 2016 and 2018, Blumenstock et al. (2020) also find that the introduction of a new phone tower led to an increase in household income of 17 percent, and increased household expenditures by 10 percent.

[18] Data on 2G coverage are also provided in the Mobile Coverage Maps database and by the mobile operators.

[19] The self-reported ownership of cellphone or Internet access is measured by a positive expenditure on cellphone or Internet subscriptions.

The analysis also examined the results on various subsamples (Table 4). First, the sample was split into rural and urban areas. 3G coverage is significantly and positively correlated with consumption and negatively associated with poverty only for urban households (Table 4, panel a). Interestingly, this correlation is particularly pronounced for food consumption among urban households while 3G coverage is significantly and positively correlated with non-food consumption for rural households. The sample is also separated according to whether household consumption is below or above the median consumption level (in each survey). This exercise reveals that while the effect of 3G coverage is positive and significant for non-food consumption for poorer households, these effects lose statistical significance for other measures of welfare, which is driven partly by a smaller sample size (Table 4, panel b).

[Table 4]

The sample is likewise split by gender and age. The positive effects of 3G coverage on non-food consumption are particularly pronounced amongst man-headed households. Splitting the sample by age using age 50 as a threshold (roughly the median age of household heads) reveals that the positive welfare effects of 3G coverage are more evident among households headed by younger people.

A potential mechanism through which mobile broadband Internet translates into improvements in welfare may be the impact on labor outcomes. The expansion of digital infrastructure and access to the Internet may not only help the creation of jobs in the ICT sector, but also reduce transaction costs for people in finding jobs or productive inputs or improve labor productivity (World Bank 2016). The analysis has examined the relationship between 3G coverage and four different labor outcomes: (1) employment, (2) wage and salaried employment, (3) formal employment, and (4) earning per month or wage.[20] The effect of mobile broadband technologies on wage/salaried or formal employment is of particular interest because a shift away from informal, self-employment toward more productive wage/salaried or formal employment in private and public services is deemed a potential pathway to reducing poverty rates in Africa (World Bank 2016, 2019). To test this causal channel, equation 1 is estimated once again, using labor outcomes as the dependent variable.

The analysis shows that 3G coverage is positively correlated with wage/salaried employment, formal employment and earning per month, although the effects on wage/salaried employment and earning become insignificant with the additional set of controls, which implies that these relationships may be confounded by other demographic and geographical factors (Table 5). 3G coverage does not have a significant impact on overall employment. These findings are consistent with other studies (e.g., Bahia et al. 2020; Hjort and Poulsen 2019) showing similar results: that access to the Internet translates into increased employment in wage or higher-skilled jobs. Our finding draws attention to the potential role that DTs can play in improving labor outcomes – and particularly, employment in "better" jobs.

5. Conclusion

[20] For this analysis, an employed individual is an individual of working age (15–64) who had worked at least one hour during the seven days previous to the interview. Wage and salaried employment includes those workers who work in a place that is not their own farm or in a business not run by their own household. Formal employment is defined as those workers whose employers or company holds a national identification number and accounting. Wage is derived based on the question in the 2017–18 ELEPS which asked how much a person earned in the last 12 months.

Despite the potential for development, evidence on the effects of Internet access on household welfare remains scarce. Most studies on digital technologies focus on cellphone (2G) access, while the studies that look at broadband tend to focus on fixed rather than mobile broadband. Yet, it is through mobile broadband that most people in African countries use the Internet (ITU 2019).

This paper provides new evidence on the positive impacts of mobile broadband coverage on household welfare in Senegal. It uses rich data available from household consumption surveys to analyze the implications of different types of technologies for welfare in 2011–18. To accomplish this, the analysis integrates household locations with data from maps of the terrestrial backbone networks and 2G, 3G, and 4G coverage maps. This allows an examination of the impact of both fixed and mobile broadband infrastructure on household consumption and poverty. The results show that mobile broadband coverage is positively associated with the levels of household consumption in Senegal. The welfare effect of 3G coverage is evident in both urban and rural areas (though its magnitude appears to be larger in urban areas), and particularly among young man-headed households. However, the analysis does not find sufficient evidence to suggest that fixed broadband has an independent impact on consumption or poverty. The analysis also shows some evidence that one of the causal mechanisms through which mobile broadband coverage yields welfare gains is its impact on labor outcomes.

In Senegal, as in other African countries, mobile broadband is the dominant channel through which people access the Internet. A recent estimate suggests that 98.7 percent of Internet users in Senegal access the Internet through mobile phones (ARTP 2019). Reliable, timely evidence of the potential impact of mobile broadband on welfare is key to comprehensive policy discussions on digital technologies. The findings of this study, which shows that mobile broadband coverage can have positive effects on consumption and poverty reduction, provide important evidence for policy makers on the potential spillovers of connectivity.

In particular, this evidence can be useful in informing the cost-benefit analysis of policies aimed at achieving universal Internet access. Network coverage is limited in African countries, especially in rural areas, where 82 percent of the extreme poor live and earn their livelihoods primarily from subsistence farming. While fixed broadband access is important for businesses (Fernandes et al. 2017; Hjort and Poulsen 2019), the evidence presented in this paper showcases the concrete benefits of mobile broadband for household welfare, highlighting its potential as a pathway to achieve universal coverage. Overall, improving the availability of affordable digital infrastructure in rural areas is key to avoiding the risk of a widening digital divide between urban and rural areas.

A related point refers to the importance of a lack of competition among service providers, which has been found as one of the main determinants—in addition to accessibility costs and market size—of the large disparity in cellphone coverage systems in Sub-Saharan Africa (Buys et al. 2009). The importance of competitive environments in digital infrastructure is relevant in Senegal, where Orange-Sonatel was the only 4G provider up to 2018–19. The need for competition to exploit fully the potential of digital technologies is highlighted by studies showing that increased competition in digital infrastructure, such as a higher number of mobile operators and the reduction in the market power of broadband monopolies, has measurable impacts on welfare by reducing prices and incentivizing new entrants (Decoster et al. 2019; Rodríguez-Castelán et al. 2019).

As this paper shows, mobile broadband can serve as a welfare-enhancing mechanism. Future work should focus on a better understanding of the uses of mobile Internet by households, such as in leisure versus productive activities (for example, job searches), as well as on the role of accessible content. Additionally, subsequent research may shed light on the implications of mobile broadband as private and public platforms, including mobile money and e-government applications, which, in the region, now tend to be based mostly on 2G technology.

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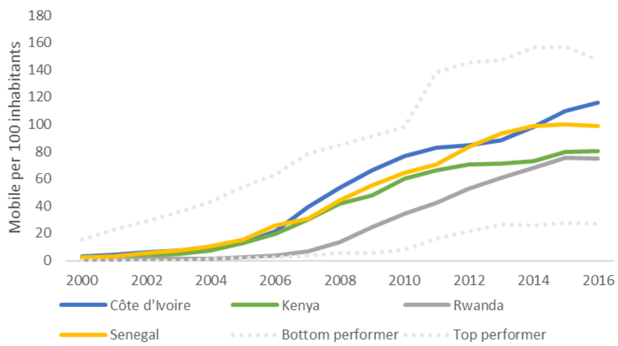
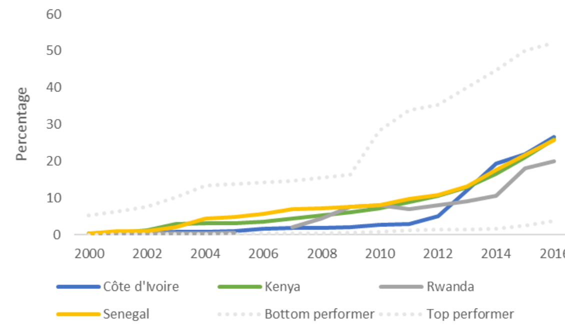
Figure 1 and Map 1

Figure 1. Mobile cellular subscriptions and Internet use in Senegal relative to peers in Sub-Saharan Africa

a. Mobile cellular subscriptions, 2000–16 (per 100 inhabitants)



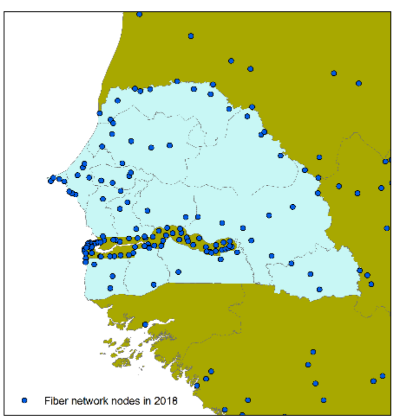
b. Individuals using the Internet, 2000–16 (% of the population)



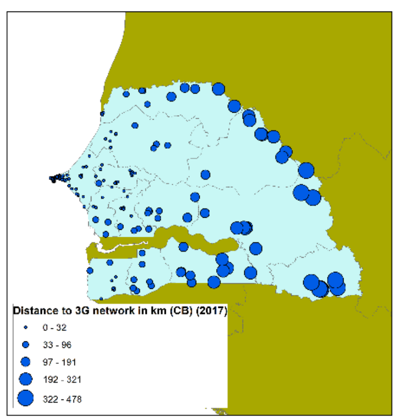
Source: World Bank estimates based on 2018 data of WDI (World Development Indicators) (database), World Bank, Washington, DC, http://data.worldbank.org/products/wdi.
Note: Dashed lines represent the values of the countries that rank in the 95th and 5th percentile of the cumulative distribution function of the variable of interest in the group of countries that belong to the Sub-Saharan Africa region. The cumulative distribution function uses the most recent year on which information is available. For more information about the methodology, see World Bank (2018).

Map 1. Fiber-optic nodes and distance to 3G coverage, Senegal

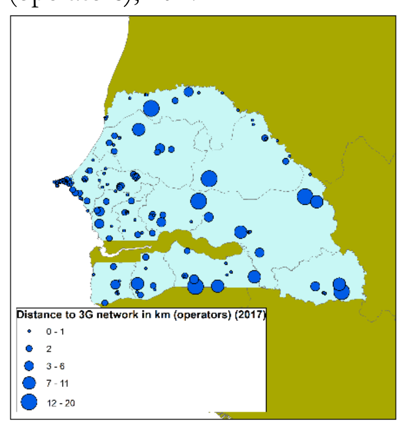
a. Fiber-optic nodes



b. Distance to 3G coverage, 2017



c. Distance to 3G coverage (operators), 2017



Sources: GPS coordinates of fiber-optic nodes: Africa Bandwidth Maps (database), Hamilton Research, Bath, UK, http://www.africabandwidthmaps.com/. Panel b: Mobile Coverage Maps (database), Collins Bartholomew, HarperCollins Publishers, Glasgow, https://www.collinsbartholomew.com/mobile-coverage-maps/. Panel c: data of Orange Sénégal; see Groupe Sonatel, Dakar, at https://www.sonatel.sn/.
Note: Distance is expressed in kilometers.

Tables

Table 1. Descriptive statistics, 2011 ESPS-II and 2017–18 ELEPS

a. 2011 ESPS-II

Variable	*N*	*Mean*	*SD*	*Min*	*Max*
Log of total consumption	5953	12.529	0.695	9.393	15.543
Log of food consumption	5953	11.845	1.226	0	14.787
Log of nonfood consumption	5953	11.61	0.915	8.969	15.317
Household size	5953	12.625	6.738	1	69
Married monogamist	5953	0.474	0.499	0	1
Married polygamist	5953	0.384	0.486	0	1
Single	5953	0.015	0.122	0	1
Widowed	5953	0.109	0.311	0	1
Divorced	5953	0.018	0.134	0	1
Literacy	5920	0.494	0.5	0	1
Wealth index	5825	0.058	1.348	-2.855	3.169
Female	5953	0.243	0.429	0	1
Access to electricity	5953	0.514	0.5	0	1
Elevation	5952	26.909	24.074	0.786	433.25
Nighttime light	5952	5.211	9.304	−0.141	51.626
Road density	5952	4529.376	7560.82	0	27000
Urban	5953	0.433	0.496	0	1
Connected to fiber-optic nodes	5952	0.049	0.215	0	1

b. 2017–18 ELEPS

Variable	*N*	*Mean*	*SD*	*Min*	*Max*
Log of total consumption	1065	12.627	0.747	8.85	15.748
Log of food consumption	1065	11.798	0.912	5.892	15.051
Log of nonfood consumption	1065	11.964	0.891	8.603	15.446
Employment*	6014	0.688	0.463	0	1
Wage work*	3076	0.236	0.425	0	1
Formal work*	1925	0.069	0.253	0	1
Log of wage*	1382	10.696	1.425	1.099	19.172
Household size	1065	11.179	7.709	1	61
Married monogamist	1060	0.617	0.486	0	1
Married polygamist	1060	0.247	0.431	0	1
Single	1060	0.013	0.114	0	1
Widowed	1060	0.106	0.308	0	1
Divorced	1060	0.014	0.117	0	1
Literacy	971	0.481	0.5	0	1
Wealth index	1013	0.198	1.188	-2.855	2.861
Female	1059	0.235	0.424	0	1
Access to electricity	1065	0.487	0.5	0	1
Elevation	1065	30.516	29.613	0	250.267
Nighttime light	1065	5.71	9.793	0.059	57.025
Road density	1065	4381.883	7725.894	0	27000
Urban	1065	0.466	0.499	0	1
Connected to fiber-optic nodes	1065	0.035	0.184	0	1
3G coverage	1065	0.782	0.413	0	1

Note: Max = maximum. Min = minimum. N = number. SD = standard deviation. *individual level

Table 2. Impact of fiber optics and 3G coverage on consumption and poverty

Dependent variable	*Total consumption*		*Food consumption*		*Nonfood consumption*		*Poverty ($1.9)*		*Poverty ($3.2)*	
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Connection	0.177*	-0.013	0.146**	0.006	0.258*	-0.001	-0.019	-0.006	-0.077	0.017
Fiber optic	(0.094)	(0.045)	(0.068)	(0.075)	(0.144)	(0.051)	(0.045)	(0.037)	(0.071)	(0.040)
Observations	7,017	6,725	7,017	6,725	7,017	6,725	7,017	6,725	7,017	6,725
R-squared	0.007	0.567	0.001	0.148	0.040	0.663	0.000	0.218	0.004	0.312
3G coverage	0.679***	0.134**	0.547***	0.053	0.876***	0.232***	-0.251***	-0.102**	-0.366***	-0.076
Mobile broadband	(0.083)	(0.065)	(0.137)	(0.113)	(0.096)	(0.075)	(0.054)	(0.046)	(0.046)	(0.063)
Observations	1,065	931	1,065	931	1,065	931	1,065	931	1,065	931
R-squared	0.141	0.607	0.061	0.283	0.165	0.649	0.085	0.301	0.095	0.359
Additional control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: Standard errors reported in parentheses are clustered by enumeration areas. All regressions include year fixed effects. Additional controls include: (a) household-level controls, including household size and marital status, sex and literacy of household heads, household access to electricity, and dwelling characteristics (as measured in the wealth index), (b) spatial controls, such as elevation, nighttime light luminosity, and road density; and (c) urban-rural and region dummy variables.
*** p < .01 ** p < .05 * p < .1.

Table 3. Impact of fiber optics and 3G coverage on consumption and poverty (instrumental variable approach)

Dependent variable	*Total consumption*	*Food consumption*	*Nonfood consumption*	*Poverty ($1.9)*	*Poverty ($3.2)*
Model	(1)	(2)	(3)	(4)	(5)
3G coverage	0.205**	−0.160	0.505***	-0.146**	-0.118
Mobile broadband	(0.097)	(0.173)	(0.119)	(0.067)	(0.091)
Observations	1,059	1,059	1,059	1,059	1,059
R-squared	0.543	0.255	0.568	0.280	0.309

Note: Standard errors reported in parentheses are clustered by enumeration areas. Distance to 3G coverage in neighboring areas is used as an instrument for 3G coverage. All regressions also include an additional set of exogenous control variables: household size, sex of household heads, elevation, and urban-rural and region dummy variables.
*** p < .01 ** p < .05 * p < .1.

Table 4. Impact of fiber optics and 3G access on consumption and poverty by group

a. Rural vs. urban

Dependent variable	*Total consumption*		*Food consumption*		*Nonfood consumption*		*Poverty ($1.9)*		*Poverty ($3.2)*	
Model	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*	*Urban*
Connection	0.131	-0.001	0.210	0.038	0.121**	0.002	-0.133**	0.009	-0.051	-0.013
Fiber optics	(0.082)	(0.044)	(0.143)	(0.072)	(0.061)	(0.054)	(0.066)	(0.037)	(0.064)	(0.035)
Observations	3,123	3,602	3,123	3,602	3,123	3,602	3,123	3,602	3,123	3,602
R-squared	0.312	0.535	0.140	0.110	0.442	0.579	0.176	0.285	0.232	0.349
3G coverage	0.070	0.373***	-0.191	0.500***	0.308***	0.279	-0.071	-0.202*	-0.045	-0.298***
Mobile broadband	(0.089)	(0.137)	(0.152)	(0.146)	(0.091)	(0.214)	(0.068)	(0.108)	(0.092)	(0.111)
Observations	309	622	309	622	309	622	309	622	309	622
R-squared	0.381	0.600	0.238	0.294	0.420	0.630	0.245	0.439	0.279	0.464

b. Low vs. high consumption

Dependent variable	*Total consumption*		*Food consumption*		*Nonfood consumption*	
Model	*Low*	*High*	*Low*	*High*	*Low*	*High*
Connection	0.013	-0.036	0.041	-0.012	0.013	-0.018
Fiber optics	(0.047)	(0.044)	(0.101)	(0.059)	(0.055)	(0.064)
Observations	3,763	2,962	3,763	2,962	3,763	2,962
R-squared	0.281	0.382	0.062	0.131	0.472	0.495
3G coverage	0.064	0.164*	-0.029	0.157	0.163**	0.267*
Mobile broadband	(0.059)	(0.089)	(0.133)	(0.106)	(0.069)	(0.151)
Observations	410	521	410	521	410	521
R-squared	0.373	0.377	0.171	0.159	0.432	0.469

c. Men vs. women

Dependent variable	*Total consumption*		*Food consumption*		*Nonfood consumption*		*Poverty ($1.9)*		*Poverty ($3.2)*	
Model	*Men*	*Female*	*Men*	*Female*	*Men*	*Female*	*Men*	*Female*	*Men*	*Female*
Connection	-0.037	0.025	0.001	0.002	-0.045	0.055	-0.019	0.030	0.041	-0.011
Fiber optics	(0.059)	(0.048)	(0.103)	(0.071)	(0.068)	(0.060)	(0.047)	(0.029)	(0.047)	(0.055)
Observations	4,985	1,740	4,985	1,740	4,985	1,740	4,985	1,740	4,985	1,740
R-squared	0.553	0.575	0.136	0.206	0.655	0.658	0.224	0.175	0.295	0.345
3G coverage	0.120	0.082	0.001	0.123	0.236***	0.100	-0.088	0.023	-0.111	0.073
Mobile broadband	(0.073)	(0.141)	(0.128)	(0.214)	(0.090)	(0.157)	(0.053)	(0.068)	(0.075)	(0.141)
Observations	653	278	653	278	653	278	653	278	653	278
R-squared	0.614	0.586	0.299	0.259	0.645	0.690	0.328	0.275	0.361	0.414

d. Age

Dependent variable	*Total consumption*		*Food consumption*		*Nonfood consumption*		*Poverty ($1.9)*		*Poverty ($3.2)*	
Model	*Below 50*	*Above 50*	*Below 50*	*Above 50*	*Below 50*	*Above 50*	*Below 50*	*Above 50*	*Below 50*	*Above 50*
Connection	0.040	-0.031	0.109	-0.057	0.109	-0.038	0.054	-0.018	-0.023	0.040
Fiber optics	(0.083)	(0.042)	(0.160)	(0.091)	(0.093)	(0.050)	(0.043)	(0.035)	(0.059)	(0.047)
Observations	3,315	3,410	3,315	3,410	3,315	3,410	3,315	3,410	3,315	3,410
R-squared	0.579	0.572	0.136	0.193	0.667	0.670	0.245	0.224	0.330	0.310
3G coverage	0.250***	-0.023	0.181	-0.205	0.370***	0.070	-0.114	-0.082	-0.102	-0.055
Mobile broadband	(0.095)	(0.112)	(0.114)	(0.246)	(0.110)	(0.110)	(0.072)	(0.068)	(0.084)	(0.102)
Observations	451	480	451	480	451	480	451	480	451	480
R-squared	0.661	0.598	0.423	0.283	0.672	0.658	0.353	0.345	0.423	0.363

Note: Standard errors reported in parentheses are clustered by enumeration areas. All regressions include year fixed effects as well as the additional set of controls: (a) household-level controls, including household size and marital status, sex and literacy of household heads, household access to electricity, and dwelling characteristics (as measured in the wealth index), (b) spatial controls, such as elevation, nighttime light luminosity, and road density; and (c) urban-rural and region dummy variables. Note that Panel *b* does not report results for poverty because after splitting the sample based on high vs. low consumption levels, there is very little variation in the status of poverty.
*** p < .01 ** p < .05 * p < .1.

Table 5. Impact of fiber optics and 3G access on employment

Dependent variable	*Employment*		*Wage employment*		*Formal employment*		*Wage*	
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
3G coverage	0.010	0.010	0.136***	0.019	0.075***	0.045**	0.431**	0.034
Mobile broadband	(0.061)	(0.070)	(0.041)	(0.060)	(0.014)	(0.022)	(0.178)	(0.200)
Observations	6,014	5,483	3,076	2,610	1,925	1,829	1,382	1,309
R-squared	0.000	0.118	0.018	0.145	0.013	0.088	0.011	0.162
Additional control variables	No	Yes	No	Yes	No	Yes	No	Yes

Note: Standard errors reported in parentheses are clustered by enumeration areas. All regressions include year fixed effects. Additional controls include (a) household-level controls, including household size and marital status, sex and literacy of household heads, household access to electricity, and dwelling characteristics (as measured in the wealth index), (b) spatial controls, such as elevation, nighttime light luminosity, and road density; and (c) urban-rural and region dummy variables. *** p < .01 ** p < .05 * p < .1.

Appendix A

This appendix provides the results of the robustness checks. Table A.1 shows the results of the first-stage regression in the two-stage least squares regressions. As seen in the table, the instrumental variable (the 3G distance index) is strongly negatively correlated with the endogenous variable of interest (3G coverage). As reported in the main text, the main results on 3G coverage are robust to the independent variable specification.

The analysis also ran a number of robustness checks. First, a test was run to determine if the main results are sensitive to whether the treatment variable is lagged or not. The test found that the contemporaneous effects of connectivity to fiber-optic networks or 3G coverage are almost identical to the lagged effects (see Table A.2). We also test how sensitive our estimates are to sampling weights. All our results are based on regressions weighted by sampling weights to account for any bias arising from the sampling. That said, our results remain stable and consistent regardless of whether sampling weights are applied or not. Tables A.3 and A.4 replicate our main results from Tables 2 and 3 but without weights. The results do not change significantly without weights. According to our unweighted regressions, 3G coverage is associated with a 18 percent increase in total consumption and a 7 percent decrease in extreme poverty rate.

Second, to account for the possibility that the estimated effects of 3G coverage are confounded by other distribution terminal infrastructure, the analysis controlled for connectivity to fiber-optic networks and 2G coverage to isolate the effects of mobile broadband Internet from fixed broadband Internet and mobile phone access. The main results do not change after the analysis controlled for these variables (see Table A.5). Third, the effects are robust to controls on the self-reported use of cellular services or the Internet (see Table A.6). This finding means that the welfare effects of 3G mobile coverage are not limited to those who use cellular phones or the Internet at home. Instead, there may be some spatial spillover effects of 3G infrastructure that benefit not only individuals, but also communities covered by 3G.

Table A.7 reports the effects of 4G coverage on welfare. As discussed in the main text, 4G coverage is not within the scope of the analysis because 4G coverage was still limited during the period of the study (2011–18). However, there was some 4G coverage in urban areas in 2017, and the analysis tested whether 4G coverage area is correlated with welfare in these areas. It found a positive relationship between 4G coverage and welfare, but this relationship is not robust to the inclusion of the additional set of demographic and geographical controls.

In terms of fixed broadband Internet, it is plausible that the (null) findings are an artifact of the somewhat arbitrary distance threshold that has been relied on to define whether households are connected to fixed broadband Internet. The main results use 1 kilometer as a distance threshold to determine whether households are sufficiently close to fiber-optic networks to benefit from faster Internet, but the distance threshold is varied from 400 meters to 3 kilometers in increments of 200 meters. No significant effect of connectivity to fiber-optic networks is found on total consumption across different distance thresholds (Figure A.1)

Table A.1. First-stage regression outputs

Variable	*Coefficients*	*Standard error*	*t-statistics*
3G distance index	−0.036	0.003	−11.490
Household size	0.001	0.001	1.390
Female	0.007	0.022	0.310
Urban	0.149	0.052	2.880
Elevation	−0.001	0.001	−0.680
Region dummies			
Region 2	0.204	0.047	4.310
Region 3	0.162	0.066	2.460
Region 4	0.153	0.180	0.850
Region 5	0.205	0.048	4.280
Region 6	−0.135	0.143	−0.940
Region 7	−0.001	0.268	0.000
Region 8	−0.004	0.107	−0.030
Region 9	0.495	0.069	7.180
Region 10	−0.017	0.015	−1.140
Region 11	0.260	0.092	2.820
Region 12	−0.014	0.189	−0.070
Region 13	−0.023	0.116	−0.200
Region 14	0.103	0.041	2.500
Region 15	−0.008	0.130	−0.060

Note: Adj R-squared = 0.69. F-statistics = 0.000.

Table A.2. Contemporaneous impact of fiber optics and 3G coverage on consumption and poverty

Dependent variable	*Total consumption*		*Food consumption*		*Nonfood consumption*		*Poverty ($1.9)*		*Poverty ($3.2)*	
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Connection	0.272***	0.022	0.225***	0.041	0.368**	0.020	-0.036	-0.006	-0.119*	-0.010
Fiber optics	(0.101)	(0.045)	(0.076)	(0.070)	(0.144)	(0.048)	(0.041)	(0.032)	(0.067)	(0.039)
Observations	7,017	6,725	7,017	6,725	7,017	6,725	7,017	6,725	7,017	6,725
R-squared	0.011	0.567	0.002	0.148	0.044	0.663	0.000	0.218	0.005	0.312
3G coverage	0.696***	0.139**	0.611***	0.044	0.875***	0.244***	-0.282***	-0.147***	-0.358***	-0.070
Mobile broadband	(0.088)	(0.064)	(0.159)	(0.120)	(0.100)	(0.074)	(0.055)	(0.050)	(0.050)	(0.063)
Observations	1,065	931	1,065	931	1,065	931	1,065	931	1,065	931
R-squared	0.127	0.607	0.066	0.283	0.141	0.649	0.092	0.307	0.077	0.359
Additional control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: Standard errors reported in parentheses are clustered by enumeration areas. All regressions include year fixed effects. Additional controls include (a) household-level controls, including household size and marital status, sex and literacy of household heads, household access to electricity, and dwelling characteristics (as measured in the wealth index), (b) spatial controls, such as elevation, nighttime light luminosity, and road density; and (c) urban-rural and region dummy variables. *** p < .01 ** p < .05 * p < .1.

Table A.3. Impact of fiber optics and 3G coverage on consumption and poverty without sampling weights

Dependent variable	*Total consumption*		*Food consumption*		*Nonfood consumption*		*Poverty ($1.9)*		*Poverty ($3.2)*	
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
Connection	0.281***	0.023	0.160**	0.023	0.412***	0.030	-0.071***	-0.013	-0.134***	-0.009
Fiber optics	(0.042)	(0.026)	(0.076)	(0.076)	(0.061)	(0.033)	(0.014)	(0.013)	(0.026)	(0.020)
Observations	7,017	6,725	7,017	6,725	7,017	6,725	7,017	6,725	7,017	6,725
R-squared	0.046	0.519	0.004	0.061	0.093	0.658	0.007	0.157	0.018	0.309
3G coverage	0.753***	0.169**	0.545***	0.142	0.963***	0.241***	-0.192***	-0.070*	-0.340***	-0.064
Mobile broadband	(0.092)	(0.067)	(0.118)	(0.094)	(0.106)	(0.090)	(0.040)	(0.037)	(0.045)	(0.057)
Observations	1,065	931	1,065	931	1,065	931	1,065	931	1,065	931
R-squared	0.106	0.622	0.044	0.286	0.125	0.656	0.067	0.243	0.081	0.358
Additional control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: Standard errors reported in parentheses are clustered by enumeration areas. All regressions include year fixed effects. Additional controls include (a) household-level controls, including household size and marital status, sex and literacy of household heads, household access to electricity, and dwelling characteristics (as measured in the wealth index), (b) spatial controls, such as elevation, nighttime light luminosity, and road density; and (c) urban-rural and region dummy variables.
*** p < .01 ** p < .05 * p < .1.

Table A.4. Impact of fiber optics and 3G coverage on consumption and poverty (instrumental variable approach) without sampling weights

Dependent variable	*Total consumption*	*Food consumption*	*Nonfood consumption*	*Poverty ($1.9)*	*Poverty ($3.2)*
Model	(1)	(2)	(3)	(4)	(5)
3G coverage	0.284**	0.023	0.525***	-0.052	-0.137
Mobile broadband	(0.137)	(0.168)	(0.167)	(0.046)	(0.098)
Observations	1,059	1,059	1,059	1,059	1,059
R-squared	0.543	0.276	0.562	0.214	0.301

Note: Standard errors reported in parentheses are clustered by enumeration areas. Distance to 3G coverage in neighboring areas is used as an instrument for 3G coverage. All regressions also include an additional set of exogenous control variables: household size, sex of household heads, elevation, and urban-rural and region dummy variables.
*** p < .01 ** p < .05 * p < .1.

Table A.5. Impact of 3G coverage on consumption and poverty after controlling for connection to fiber-optic transmissions and 2G coverage

Dependent variable	*Total consumption*		*Food consumption*		*Nonfood consumption*		*Poverty ($1.9)*		*Poverty ($3.2)*	
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
3G coverage	0.691***	0.130*	0.551***	0.060	0.894***	0.220***	-0.264***	-0.099**	-0.372***	-0.072
Mobile broadband	(0.086)	(0.066)	(0.145)	(0.116)	(0.100)	(0.076)	(0.056)	(0.048)	(0.048)	(0.065)
Observations	1,065	931	1,065	931	1,065	931	1,065	931	1,065	931
R-squared	0.141	0.608	0.062	0.283	0.166	0.650	0.088	0.301	0.095	0.359
Additional control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: Standard errors reported in parentheses are clustered by enumeration areas. All regressions include controls for connectivity to fiber-optic networks and 2G coverage. Additional controls include (a) household-level controls, including household size and marital status, sex and literacy of household heads, household access to electricity, and dwelling characteristics (as measured in the wealth index), (b) spatial controls, such as elevation, nighttime light luminosity, and road density; and (c) urban-rural and region dummy variables.
*** p < .01 ** p < .05 * p < .1.

Table A.6. Impact of 3G coverage on consumption and poverty after controlling for the use of cellphones and the Internet

Dependent variable	*Total consumption*	*Food consumption*	*Nonfood consumption*	*Poverty ($1.9)*	*Poverty ($3.2)*
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
3G coverage	0.133**	0.056	0.231***	-0.101**	-0.074
Mobile broadband	(0.065)	(0.113)	(0.075)	(0.046)	(0.064)
Observations	931	931	931	931	931
R-squared	0.618	0.290	0.660	0.301	0.359

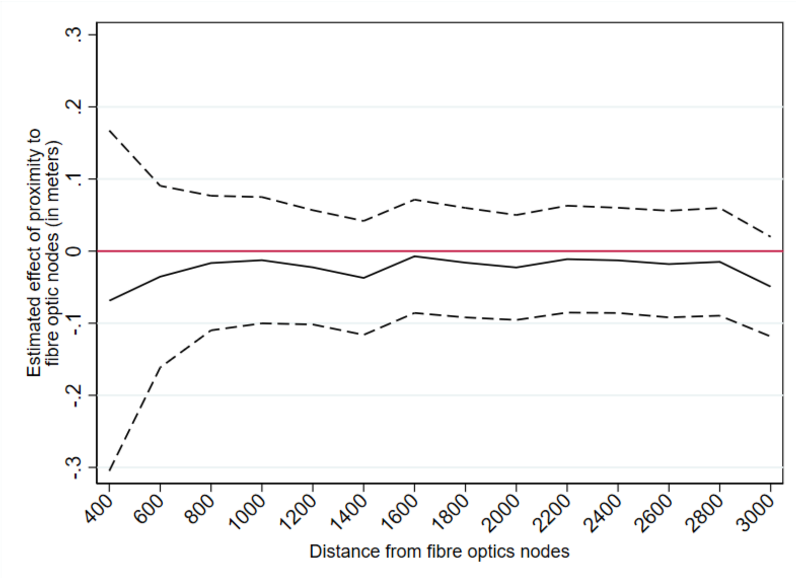
Note: Standard errors reported in parentheses are clustered by enumeration areas. All regressions control for use of cellphone or Internet (which is measured by positive expenditure on cellular or Internet subscriptions) and additional controls including (a) household-level controls, including household size and marital status, sex and literacy of household heads, household access to electricity, and dwelling characteristics (as measured in the wealth index), (b) spatial controls, such as elevation, nighttime light luminosity, and road density; and (c) urban-rural and region dummy variables.
*** p < .01 ** p < .05 * p < .1.

Table A.7. Impact of 4G coverage on consumption and poverty

Dependent variable	*Total consumption*		*Food consumption*		*Nonfood consumption*		*Poverty ($1.9)*		*Poverty ($3.2)*	
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
4G coverage	0.574***	0.013	0.309***	0.067	0.830***	0.072	-0.176***	0.001	-0.319***	0.012
Mobile broadband	(0.093)	(0.085)	(0.086)	(0.104)	(0.116)	(0.094)	(0.058)	(0.039)	(0.064)	(0.072)
Observations	704	622	704	622	704	622	704	622	704	622
R-squared	0.156	0.593	0.046	0.280	0.206	0.628	0.085	0.427	0.124	0.441
Additional control variables	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Note: Standard errors reported in parentheses are clustered by enumeration areas. Additional controls include (a) household-level controls, including household size and marital status, sex and literacy of household heads, household access to electricity, and dwelling characteristics (as measured in the wealth index), (b) spatial controls, such as elevation, nighttime light luminosity, and road density; and (c) urban-rural and region dummy variables. The analysis is restricted to urban areas because there was almost no 4G coverage in rural areas in 2017.
*** p < .01 ** p < .05 * p < .1.

Figure A.1. Proximity to fiber-optic transmission nodes and the estimated effects on total consumption



Note: The figure reports the estimated effects of proximity to fiber-optic transmission nodes with varying distance thresholds ranging from 400 meters to 3 kilometers. The solid black line shows the estimated coefficients on connectivity to fiber-optic networks (with a varying distance threshold). The dashed lines show 95 percent confidence intervals.