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From Phone Access to Food Markets: Is Mobile Connectivity Transforming West-African Livelihoods ?

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Abstract

This paper investigates the impact of mobile connectivity on food market prices and household demand for food products in the West African Economic and Monetary Union (WAEMU) region. Leveraging data from harmonized World Bank LSMS household surveys across eight WAEMU countries, this study includes 59,319 households and 146 food products across 4,983 enumeration areas, with data gathered in 2018-2019. … /…

Keywords: Connectivity, digital, mobile phone, mobile money, agricultural markets, household, food consumption.
JEL : O13, O33, Q11, Q13

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../… By using exposure to lightning strikes as an instrumental variable for cell tower coverage, we find that mobile connectivity reduces food price dispersion by spurring food prices catch-up in rural areas. Greater market demand for food products and lower reliance on self-consumption of food produced by rural households appear to be the drivers of this observed convergence in food price. Additionally, enhanced financial inclusion through mobile money and diversification of income sources through off-farm and non-agricultural activities are identified as key enablers of these observed changes. Overall, these results suggest that the digitalization of rural areas stimulates the transition from a subsistence to a market economy, thereby accelerating rural transformations, albeit with the added risk of leaving unconnected households behind.

I. INTRODUCTION

The persistence of low productivity and pervasiveness of agricultural market failures in sub-Saharan Africa represent a critical obstacle to structural transformations over recent decades, and a cause of premature deindustrialization in some cases (Rodrik, 2016; De Janvry & Sadoulet, 2022; Suri & Udry, 2022; Huneeus & Rogerson, 2023). Reducing information search, distance, and other transaction costs is therefore a major challenge for African agricultural markets and rural households (HH) alike, often plagued with missing or remote infrastructures, harsh climatic conditions, insecurity, and underdeveloped financial systems (Aker & Mbiti, 2010; Aker & Cariolle, 2023). One direct consequence of these market failures is the spatial and temporal dispersion of agricultural commodity prices, which reflects the poor allocation of supply across local markets by misinformed farmers and traders. Another consequence is low agricultural productivity and a lack of diversified revenues, as well as persistent food insecurity, especially in rural areas. These problems are particularly acute in West African countries, which rely heavily on rainfed agriculture and are strongly exposed to rising climatic, geopolitical, and socio-political risks with adverse effects on food security, food prices, and productivity (De Longueville et al., 2020; Sers & Mughal, 2020; Bouët et al., 2023; McGuirk & Nunn, 2023, 2024).

By bringing together information, communication and financial functions in a simple and affordable device, mobile phones, whose diffusion across the region has been unprecedented over the last two decades, are having a transformative impact on agricultural market functioning and rural livelihoods (Aker & Mbiti, 2010; Aker & Cariolle, 2023). Mobile phone users can access information on prices, technologies, and job opportunities in a timely manner through low-cost digitized market information, agricultural extension services, or by simply communicating with their private network. Moreover, with the rollout of mobile money systems, and more recently of mobile banking services, mobile phones have also filled the missing link between formal financial institutions and unbanked HHs, by providing a cheap, instantaneous, and effective way of storing, converting, and transferring money (Suri et al., 2023; Aker & Cariolle, 2023). Importantly, these changes are within the reach of any owners of "feature phones" with basic literacy skills, covered by the GSM network but not necessarily by 3G or higher generation mobile internet network.

This paper therefore aims to delve into the transformations brought by mobile phone diffusion across urban and rural communities in West -Africa as well as individual households. This study consists of a large-scale micro-level analysis of the effect of mobile connectivity and adoption on food market prices and HH livelihoods in both rural and urban areas of the eight West African Economic and Monetary Union (WAEMU) member countries – Benin, Burkina Faso, Côte d'Ivoire, Guinea-Bissau, Mali, Niger, Senegal, and Togo. The World Bank's harmonized Living Standards

Measurement Study (LSMS[1]), conducted in all eight WAEMU members in 2018 and 2019, has made it possible to evaluate this contribution over an extended perimeter and for a large array of food products. In fact, the combined harmonized survey dataset covers 59,319 households (HHs) and 146 food products spread across 4,983 enumeration areas (EAs), 481 districts, and 106 regions in the WAEMU.

The paper's contribution is twofold. First, studying the nexus between mobile connectivity and food market prices over a regional multi-country scale, using microeconomic survey data and focusing on multiple food products is critical to check the external validity of results obtained at a national or local level by a large spectrum of empirical studies. Research conducted in sub-Saharan Africa and other developing regions highlight the transformative potential of mobile telephony for agricultural markets functioning and HH welfare (Aker & Mbiti, 2010; Aker & Cariolle, 2023). Existing evidence on the impact of mobile technology on West African agricultural markets is however relatively scarce, compared to Eastern or Southern Africa, with the exception of Ghana (Courtois & Subervie, 2015; Soldani et al., 2023), Burkina Faso (Maredia et al., 2018) and Niger (Aker, 2010; Aker & Fafchamps, 2014; Tack & Aker, 2015).

In this literature, supply-driven mechanisms, such as improved spatial allocation of agricultural supplies or greater farmer's bargaining power induced by better-informed farmers and traders, are often invoked to explain observed commodity price convergence patterns and the concomitant variations in farm-gate or market prices (Jensen, 2007; Svensson & Yanagizawa, 2009; Goyal, 2010; Aker, 2010; Tack & Aker, 2014; Aker & Fafchamps, 2015; Soldani et al, 2023). By contrast, the role of demand-driven mechanisms in explaining agricultural price patterns have often been overlooked, whereas their potential salience would be indicative of long-term agricultural and rural transformations (De Janvry & Sadoulet, 2022).

Yet, access to mobile phones and networks could stimulate HH food demand through larger on-farm, off-farm, and non-agricultural revenues, or through financial inclusion and improved risk management. There exists indeed a great body of evidence from countries around the world showing a positive impact of mobile connectivity on consumption patterns, suggesting that the abovementioned price dynamics could also be demand-driven (Nakasone & Torero, 2016). To cite a few, Roessler et al. (2021) found that adoption of smartphones by women in Tanzanian households raised per capita consumption by 20%. Wantchekon and Riaz (2019) found that mobile network connectivity resulted in improved food security for African HHs. A study conducted by Beuermann et al. (2012) found that mobile network coverage extension in rural villages of Peru induced an 11% increase in household expenditures. Labonne and

[1] Also referred to by the French acronym for LSMS surveys carried out in the WAEMU countries, EHCVM (*Enquête harmonisée sur les conditions de vie des ménages*)

Chase (2009) show that mobile phone ownership by farmers in rural areas of the Philippines increased household per capita consumption by 11-17%. Last, a large array of research has established that mobile phone usage, through mobile money adoption, is a powerful tool for risk-sharing and household consumption smoothing (Jack & Suri, 2014; Suri et al., 2023; Batista & Vicente, 2023). Therefore, the second and probably greatest contribution of this paper is to connect the impacts of mobile connectivity on food-product prices to HHs demand for food products and access to off-and non-farm revenue.

We adopt an instrumental variable (IV) approach similar to that adopted by Guriev et al (2021) and Manacorda and Tesei (2020), which consists in instrumenting the mobile-internet network coverage of enumeration areas (EAs) observed in 2018-2019 by their past exposure to lightning strikes over the 1998-2013 period. Exposure to lightning causes electrical surges, leading to faster wear and tear on equipment and affecting the quality of connectivity, but lightning-resistant protection for such equipment are very costly and not widely deployed in SSA (ITU, 2003; Andersen et al, 2012; Martin 2016). We also include and combine a number of control variables and fixed effects (FEs) to control for survey waves, food products, and geographical areas' (region, district or EA, depending on the outcome variable considered) unobservable characteristics. Reduced-form estimations and multiple robustness checks, with a particular emphasis on the exclusion restriction assumption, are also successfully performed and support the validity of the instrument.

Our findings give an original and coherent picture of economic transformations induced by mobile connectivity across the region. Firstly, our analysis shows that EAs covered by the mobile network observe 10 to 12%-higher food product prices compared to EAs located further away from the network, and that this effect is driven by network coverage expansion in rural areas. The consequence is a food prices catchup in rural communities, confirmed by a reduction in price dispersion at the district level. In fact, the analysis shows that a 10% increase in network coverage in a given district leads to a 5% drop in the coefficient of variation of food prices. These numbers are consistent with findings of reference empirical studies conducted on distinct specific commodities at the national or local levels throughout the region (Svensson & Yanagizawa, 2009; Aker, 2010; Nakasone, 2013; Courtois & Subervie, 2014; Aker & Fafchamps, 2015; Soldani et al., 2023).

Importantly, estimations also show that food demand explains observed price patterns. Estimations carried out at the HH level show that when a HH acquires a mobile phone in an EA covered by the mobile network, it significantly increases total spending (+18%), especially in rural areas (+63.7%), and particularly on food items (+12.8%) compared to non-food ones (+6.4%). Mobile connectivity is also found to increase both consumed and purchased food quantities, while reducing HH reliance on self-consumption. Quantities of products consumed and purchased by connected HHs indeed increase by 20% and 29%, respectively, while self-consumed quantities fall by 9%. Again, this effect of connectivity is particularly pronounced for rural HHs, who experienced a 41% and 61% increase in consumed and purchased quantities of food products, respectively, and a 19% drop in self-consumed quantities. Last, our analysis reveals that financial inclusion through mobile money adoption is a key enabler of evidenced transformations, while income diversification through increased off-farm activities and non-agricultural entrepreneurship has likely supported the demand for food products, especially in rural places.

In summary, our analysis shows that mobile connectivity has led to a spatial convergence in agricultural commodity prices, supported by an increase in HH food spending and consumption levels, diminished reliance on self-consumption, and greater access to off-farm and non-agricultural revenues. Taken together, these results indicate that West-African economies and rural HHs may be subject to profound economic transformations, prompted by the digital interconnection process in rural areas. However, an important side effect of this evidence is the negative externality of connectivity on households with no or little access to mobile phones. These households, despite being located in connected areas, do not benefit from the digital dividends of mobile technology, while they find themselves faced with a rising cost of living. Addressing the usage gap, especially in rural communities, is therefore critical to ensure that observed transformations remain inclusive.

The remainder of this article is organized as follows. Section II presents the data and the empirical strategy. Section III presents and discusses our baseline results. Section IV provides additional estimations while Section V presents the robustness analysis. Section VI concludes.

II. ESTIMATION FRAMEWORK

A. The data

This study is based primarily on cross-section data from the Harmonized Survey on Households Living Standards (EHCVM) for the eight WAEMU countries. These surveys are part of the Living Standards Measurement Study (LSMS) conducted as part of the West African Economic and Monetary Union (WAEMU) Household Survey Harmonization Project (P153702), in each of the eight member states. These surveys are nationally representative of geopolitical zones (at urban and rural levels) and were carried out in two waves (in late 2018 and spring 2019) to account for seasonality of consumption. These data cover 59,319 households (HHs), spread across 4,983 enumeration areas (EAs), 481 districts (second-level administrative divisions), and 106 regions (first-level administrative divisions) of the eight countries in the zone. In each EA, 12 randomly selected HHs are surveyed. The EHCVM data provide information on a wide range of conditions experienced by households, including rural and agricultural issues, with data collected from households/individuals, or at the community level (EA). The distribution of the sample in each country is shown in Table I below. Appendix A reports the definitions and descriptive statistics of variables used in this paper.

TABLE I. DISTRIBUTION OF THE LSMS SAMPLE IN THE WAEMU

	# HHs	# EAs	# Districts	# Regions
Benin	8,012	670	77	12
Burkina Faso	7,010	585	45	13
Côte d'Ivoire	12,992	1,084	108	33
Guinea-Bissau	5,351	450	46	9
Mali	6,602	551	55	11
Niger	6,024	504	62	8
Senegal	7,156	598	45	14
Togo	6,172	541	43	6
Total	**59,319**	**4,983**	**481**	**106**

Source: authors. Data from LSMS (World Bank).

1. Dependent variables

The analysis first focuses on the effect of mobile connectivity on food commodity market prices, observed in EAs, and on their spatial dispersion at the district level. Then, it addresses the demand channel by analyzing the effect of mobile ownership on HH's food expenditures and consumption patterns. Definitions and descriptive statistics of dependent variables are provided in Appendices A.1 and A.2, respectively.

Firstly, the analysis of commodity market price levels covers 146 food products traded in EAs across the WAEMU countries. We use the two distinct price records collected for each product by surveyors as separate dependent variables. We also conduct the analysis separately on each of the most-traded commodities in the WAEMU area (see data description in Appendix A.4).[2] As prices for a given commodity are generally available for different units of measurement (e.g. small, medium, or large mound of chili peppers), we adopt two approaches. In baseline analysis, we consider, for each commodity, the log-transformed price of the commodity/measurement-unit pair most traded across EAs (see Appendix A.4). District or region-commodity-unit FEs are then included in the econometric analysis to account for local, inherent, and unobservable differences in prices due to the nature of the considered commodity-unit pairs, so as to make prices comparable.[3]

In robustness analysis, we apply measurement-unit conversion factors provided by the WAEMU Commission to each product-unit in each EA, which makes it possible to compute the price per gram of a given commodity. Assuming that these conversion factors were accurately recorded, this approach should yield more precise and more comparable estimates since all prices are expressed in XOF per gram.[4] However, unit conversion factors are also prone to measurement errors, and therefore may add statistical noise to the analysis. For this reason, we consider this variable as supplementary and useful to check the robustness of estimated relationships.

Secondly, food price dispersion is analyzed at the district level. The geographical dispersion of prices is measured by the coefficient of variation of both non-converted and converted food prices, computed for each of the 146 commodities traded in the WAEMU.

Thirdly, in support of the previous analysis, we investigate the effect of digitalization on the demand for commodities, using measurements of food (and non-food) expenditures by households, and quantities of food (self-)consumed and purchased.[5] The analysis of quantities (self-)consumed and purchased was also possible through

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[2] In decreasing order of frequency, these commodities (units) are: salt (1 small sachet), sugar (1 kg), fresh onion (small heap), tomato paste (1 small tin), fresh tomatoes (1 small heap), fresh okra (1 small heap), imported grain/broken rice (1 kg), local long rice, red palm oil (1 litre), peanut paste (1 small sachet), potato (1 kg), and chili pepper (1 small heap).

[3] This selection of product/measurement-unit pair is based on the observed frequency of transactions in each EA/district and on the number of countries (minimum seven) where the foodstuff has been sold. See Appendix A.2.

[4] This approach also increases the sample size, since applying the former approach leads to excluding EAs using less-traded product-unit pairs. To maximize sample size, we also impute price level in EAs where conversion unit factors are missing, by applying the district-level or regional averages of conversion factors. In robustness analysis we conduct estimation on restricted sample, using converted price with original unit conversion factors (i.e. without imputed conversion factors).

[5] Food diversity, proxied by the number of (self-) consumed food products, is addressed in a supplementary way in Appendix B.5.

the commodity-unit conversion factors for non-standard units of measurement in grams, which are also available by country-region (and in some cases by district), and are reported in a relatively harmonized manner for quantities of commodities consumed/purchased by households.[6]

2. Digitalization variables

In this study, we measure the digitalization process through variables of spatial proximity to the mobile network connectivity and mobile adoption. Access to internet is also addressed in a complementary manner, but is expected to be less pivotal in West African agricultural markets, because of low internet technologies penetration in these areas (Abate et al., 2023; Aker & Cariolle, 2023).

Appendix A.3 reports descriptive statistics of the digitalization variables described below, as well as coverage maps of cell-tower proximity dummies. It shows that 90% of households have a cell phone, with an average of two cell phones per household, and that 30% of households have Internet access. In terms of network connectivity, these same households are located in EAs situated 14 km on average from the nearest 2G, 3G, or 4G (2G+) towers.

Network connectivity. We use data on the spatial deployment of 2G+ cell towers from the OpenCellID project.[7] From these data, we calculate three network connectivity variables:

- The distance from the geographic centroid of the EA to the nearest 2G+ tower, in kilometers.[8]
- A dummy variable equal to 1 if the EA centroid is within 2 km of the tower, zero otherwise.[9]
- A dummy variable equal to 1 if the EA centroid is within 5 km of the tower, zero otherwise.

When the analysis is carried out at the district level, i.e. when studying the spatial price dispersion, we calculate the 2G+ coverage as a percentage of the district's surface area.

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[6] As these conversion factors are also prone to measurement errors, we include product-measurement unit fixed effects to limit this possible source of bias.

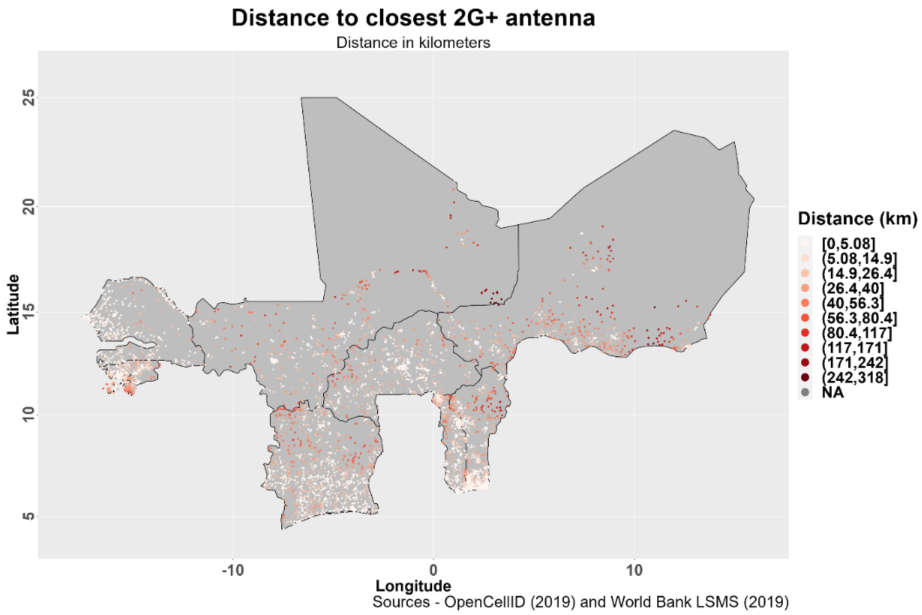
[7] https://www.opencellid.org/.

[8] Access to the 2G network is also useful for accessing lightweight Internet sites and applications (such as Facebook Free Basics) (Hatte et al., 2023). As 3G towers are more common in urban areas than 2G towers, we consider the minimum distance to all types of networks (2G, 3G, 4G) enabling internet access.

[9] We chose a rather conservative threshold for the centroid distance to the cell-tower, because we have no information about the EA actual area, which can be large in rural places, and because we are more concerned by false positive than by false negative. In robustness analysis, we complement this measure by information provided by LSMS surveyors about network signal quality.

Figure I below shows the approximate range of distance in kilometers from the center of a given EA to the closest 2G+ cell tower.

FIGURE I. MAPPING AVERAGE EA DISTANCE TO THE CLOSEST CELL TOWER IN THE WAEMU.



Adoption. HH-level digital connectivity is measured by mobile phone adoption, which is a variable equal to the number of mobile phones in the household. This variable is preferred to a dummy variable indicating the ownership of at least one cell phone in the household, as it offers greater variability (90% of households in the sample have a cell phone) and makes it possible to measure the degree of digitalization within the HH. Mobile connectivity is our main focus since mobile phones, rather than internet (30% of HH had access to Internet inside or outside their home[10]), are found to play a pivotal role in agricultural and rural development (Aker & Mbiti, 2010; Aker & Cariolle, 2023). However, in Section IV.A, we also investigate the effect of internet, and also mobile money adoption.

3. Control variables

Depending on the scale of analysis chosen – household (HH), EA, or district – we control for a number of determinants of local agricultural development. These control variables and their associated descriptive statistics are shown in Appendices A.5, and A.6.

Household-level controls. We control for the characteristics of the head of HH (HHH), i.e., gender, age, level of education and literacy, and marital status (monogamous or polygamous). We also control for HH size, access to finance, housing characteristics,

[10] This number corresponds to the 2019 average in Sub-Saharan Africa, according to the World Bank.

standard of living (through ownership of various assets, such as a television, fridge, etc.), access to electricity and sanitation infrastructure, HH exposure to idiosyncratic and covariant shocks of various kinds (health, income, climate, etc., see Appendix A.8), and the HH's farm characteristics (surface of rain-fed and irrigated plots, see Appendix A.5).

EA-level controls. We control for local economic development by density of nighttime lights, the presence of motorized collective transport in the EA, and by a set of dummy variables revealing the two main economic activities conducted in the EA. We also control for demographic characteristics of the EA – i.e., population density, number of households surveyed and EA population – and geographic characteristics – i.e., the EA's topography, whether the EA is urban or rural, its distance from the nearest city, and its altitude (Appendix A.6).

B. Empirical model and identification strategy

1. General model

In this study, we estimate the effect of digitalization ($DIG_{m,z,d}$) on agricultural development outcomes ($Y_{j,m,z,d}$), observed at the level of product *j* consumed by households *m*, traded in EA *z*, or dispersed in district *d*. The empirical analysis includes a number of control variables ($X_{m,z,d}$) and EA/district/region *z/d/r* (depending on the level of analysis of the dependent variable), survey wave *v*, and product *j* FEs ($D_{z,d,v,j}$). Digitalization ($DIG_{m,z,d}$) is considered through the lens of network connectivity in the EA or district ($CON_{z,d}$); or mobile connectivity ($CON_z \times AD_m$), i.e. mobile adoption by HHs (AD_m) in connected EAs, when the analysis is conducted at the household level.

The empirical analysis therefore proceeds with the econometric estimation of the following general function:

$$\mathrm{Y_{j,m,z,d}} = \mathrm{F}\left(\mathrm{DIG_{m,z,d}}; \mathrm{X_{m,z,d}}; \mathrm{D_{z,d,r,v,j}}\right) \qquad (1a)$$

$$\mathrm{DIG_{m,z,d}} = G\left(\mathrm{CON_{z,d}}; \mathrm{CON}_z \times \mathrm{AD}_m\right) \qquad (1b)$$

whose calibration and scale of analysis will be adapted to the agricultural outcome under consideration.

2. Identification strategy

The empirical analysis of the causal effect of digitalization on agricultural development is weakened by a simultaneity bias – agricultural development, or economic development in general, can lead to better connectivity and a greater capacity for absorption of digital technologies by households – and an omitted variable bias induced by unobservable characteristics of HHs, EAs, and districts potentially correlated with the dependent variables considered in our analysis.

To control for these potential biases, we adopt an instrumental variable approach based on Manacorda and Tesei (2020) and Guriev et al. (2021), consisting in exploiting historic EA exposure to lightning strikes to predict the extent of 2G, 3G, and 4G antenna network expansion. It is known that exposure to lightning causes electrical surges that damage mobile network infrastructure, leading to faster wear and tear on equipment and affecting the quality of connectivity (ITU, 2003; Andersen et al, 2012; Martin 2016; Manacorda & Tesei, 2020; Guriev et al, 2021). Lightning-resistant protection for such equipment does exist, but it is still very costly and not widely deployed in SSA. Thus, due to higher deployment and maintenance costs, and lower connectivity quality, we expect lower network coverage and a lower adoption rate of mobile and internet technologies in areas more exposed to this risk.

We calculate the average of daily lightning strikes recorded over the 1998-2013 period from the LIS 0.1 Degree Very High-Resolution Gridded Lightning Full Climatology (VHRFC) dataset. Lightning strikes are observed and localized by grid by the Lightning Imaging Sensor, an instrument of the Tropical Rainfall Measurement Mission (TRMM) satellite, from January 1, 1998 to December 31, 2013 (Albrecht et al., 2016).[11] We follow a similar approach to Guriev et al (2021) and weight this average by the population density in the EA, measured in 2015:

$$\text{Lightning\_risk}_z = \text{Lightning\_intensity}_z^{1998-2013} \times \frac{1}{1+\text{popdens}_z^{2015}} \quad (2)$$

$\text{Lightning\_intensity}_z^{1998-2013}$ is the average daily frequency of lightning strikes observed in EA z over the period 1998-2013, and $popdens_z^{2015}$ the population density observed in the EA in 2015. We consider the average daily lightning strike intensity (the VHRAC variable in the dataset) as a measure of structural lightning exposure, because averaging on daily basis and over a 15-year period allows purging lightning strikes resulting from within-year seasonal (rain or dry season) and between-year cyclical (e.g. caused by El Nino phenomenon) climate factors. We consider that lightning strikes exposure purged from these cyclical components matters more in operator decisions related to developing new cell towers and protecting and maintaining existing cell towers. Moreover, we also consider densely populated areas as a structural element to be accounted for, since they are associated with a higher demand for connectivity and economies of scale, and thereby expected to compensate the adverse consequences of lightning strikes on the costs of deploying, protecting, repairing, and maintaining cell towers in exposed areas. Population density is

[11] Satellite data are only publicly available for years prior to 2013. Nevertheless, calculating exposure to this hazard over a previous period is relevant if we wish to obtain an approximation of the lightning strike risk for a given area. We therefore calculated the average daily number of lightning strikes over 1998-2013 to eliminate the diurnal cycle and smooth out regions with a low lightning strike rate. After downloading the data, we extracted the average annual number of lightning strikes for each EA using three different methods. The main method used in baseline estimations involved extracting the single point value from the raster file at the centroid of each EA. Two alternative extraction methods, used in robustness checks, are presented in Appendix D.5.

therefore considered to be a weighting factor of lightning frequency (and additively as a control variable). A mapping of this exposure is provided in Figure II, which shows a lightning-strike belt covering Côte d'Ivoire, Togo and Benin. Descriptive statistics for the weighted lightning instrumental variable, and its separate components, are given in Table II.

The theoretical validity of the instrument could be called into question in the case of a direct effect of lightning exposure on agricultural activity in EAs and on household incomes and well-being, through for instance higher rainfall, and more frequent fires, or power outages. First, our approach limits potential bias by constructing the instrument from de-seasonalized lightning data dating from the period 1998-2013, hence years before the period of data collection used in the study. In addition, the estimates conducted at the EA and HH levels include district and EA FEs, respectively, thus making it possible to control for local unobservable factors such as the direct effect of weather conditions on agricultural market activity and organization at a rather disaggregated level. Moreover, we include in our model nighttime light density, which control for local economic development, including electricity access, which could be directly affected by weather shocks. For the same reason, we also control for the occurrence of various types of shocks reported by HHs (See Appendix A.8), especially droughts, irregular rains, floods, fires and landslides. Importantly, we control in robustness analysis for contemporaneous and past rainfall, and conduct additional instrument validity tests, reported in Appendixes D.6 and D.7. These tests support that the exclusion restriction is well respected.

FIGURE II. MAPPING DAILY LIGHTNING STRIKES IN THE WAEMU, 1998-2013 AVERAGE.

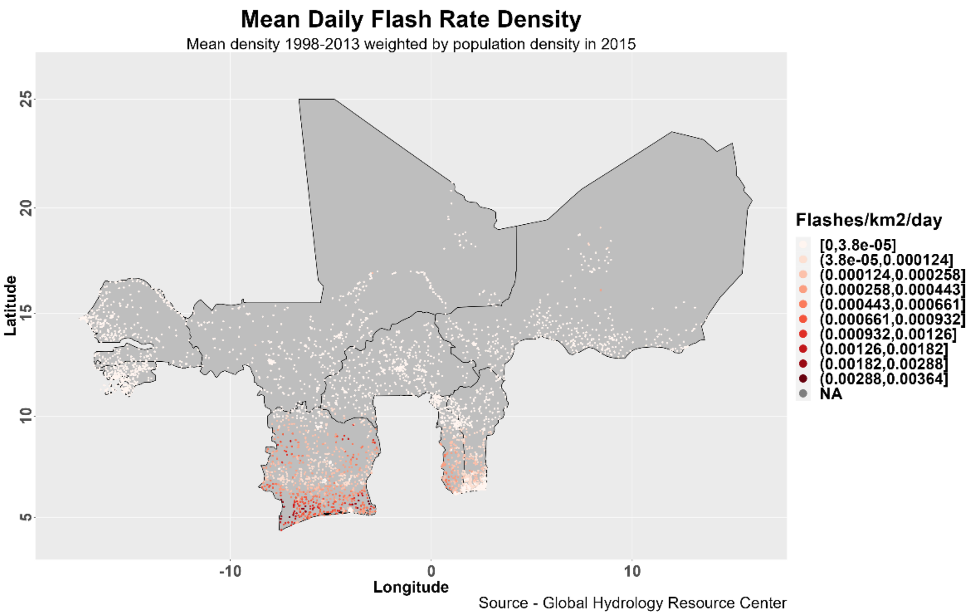


TABLE II. DESCRIPTIVE STATISTICS FOR INSTRUMENTAL VARIABLES.

Variable	# obs (#EA)	Average	Std. dev.	Min	Max
IV- Lightning risk	4,646	0.0000846	0.0002446	0	0.003641
Lightning freq 1998-2013	4,646	0.0081199	0.0166799	0	0.1143522
Pop density 2015	4,646	1171.802	3521.136	0.1317621	34944.11

Source: authors. Lightning and population data from NASA.

We then estimate the following first-stage equation at the EA level:

$$\mathrm{CON_z} = \alpha_0 + \alpha_1.\mathrm{Lightning\_risk_z} + \Gamma.\mathrm{X_z} + \Theta.\overline{\mathrm{M}_z} + \mathrm{D_t} + \mathrm{D_d} + \epsilon_\mathrm{z} \qquad (3)$$

$\mathrm{CON_z}$ is a connectivity variable, measured by the distance of the EA centroid to the nearest mobile internet antenna (2G, 3G or 4G), or by a dummy variable indicating whether the centroid is within 2 km (or 5 km) from the nearest antenna. $\mathrm{X_z}$ and $\overline{\mathrm{M}_z}$ are respectively a set of control variables for EA and HH (averaged) characteristics, presented in sub-section 3.1.3. $\mathrm{D_d}$ and $\mathrm{D_t}$ are district and survey wave FEs, respectively, controlling for unobservable heterogeneity in the district or at the time when survey waves 1 (2018) and 2 (2019) were conducted. ϵ_z is an error term. Standard errors are robust to heteroskedasticity and clustered at the district level.

The results of OLS estimations of equation (3), run with and without control variables, with district or region FEs, are shown in Table III below. Details of the estimates for the control variables are given in Appendix B.1. The results show that lightning risk significantly increases the distance of EAs from antennas, and significantly reduces the probability of being within a 2 km radius of these antennas (also 5km, see Appendix B.1). Thus, a one-standard-deviation increase in the risk of lightning strikes increases the distance to the mobile internet network by an average of 1.86 km, corresponding to a 13% increase in the average distance to these antennas (column (2)). These initial results confirm the relevance of the instrument.

TABLE III. EQUATION (3), OLS ESTIMATIONS.

	(1)	(2)	(3)	(4)	(5)	(6)
Var dep.:	Dist. network. (ln, km)			Dist < 2km (0/1)		
IV	811.5***	1229.9***	768.9***	-260.3***	-409.7***	-232.6***
	(113.6)	(152.6)	(115.9)	(48.15)	(49.04)	(38.26)
Controls	Yes	No	Yes	Yes	No	Yes
District FE	Yes	Yes	No	Yes	Yes	No
Region FE	No	No	Yes	No	No	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs. (# EA)	4,647	4,764	4657	4,646	4,763	4656
R2	0.775	0.650	0.613	0.676	0.521	0.564

Standard errors in brackets, robust to heteroskedasticity and clustered by district. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. All regressions include the population density as control, as it enters in the IV formula.

III. EMPIRICAL ANALYSIS.

We carry out an econometric analysis of the effect of digitalization on the functioning of agricultural markets, and on the consumption and purchase of agricultural commodities in the WAEMU zone.

A. Network connectivity and food product market prices

1. Model and hypothesis testing

We begin by examining the relationship between digitalization, measured by the EAs' proximity to the mobile-internet network, and the average food commodity price levels observed in the EAs. First, one can expect improved access to market price information to rationalize the spatial allocation of agricultural supply. Given the relatively higher transaction costs (linked in particular to transport) and information search costs in rural areas than in urban areas, this reallocation of supply should lead to increased (reduced) supply in markets with higher (lower) demand and higher (lower) commodity prices (Aker & Fafchamps, 2015). Numerous empirical studies carried out in rural areas of Sub-Saharan Africa tend to support this hypothesis, namely of a rise in either farmgate or market prices for agricultural products following improved HH access to ICTs (Svensson & Yanagizawa, 2009; Muto & Yamano, 2009; Courtois & Subervie, 2015; Aker & Fafchamps, 2015; Abate et al., 2023).

Second, mobile phone adoption may also have demand-side effects by increasing HH purchasing power through higher farm revenues, but also improved access to off-farm jobs, financial services, and therefore, diversified income sources. The result of these supply and demand-side mechanisms is a convergence in commodity prices between rural and urban areas, and a reduction in their spatial dispersion (Aker, 2010; Aker & Fafchamps, 2015).

We are therefore interested in the effect of mobile network connectivity on food prices by estimating the following equation using OLS, and in a subsequent subsection using 2-stage least squares (2SLS):

$$\text{Ln}\ \mathrm{P}_{z,j} = \beta_0 + \beta_1 . \mathrm{CON}_z + \Gamma . \mathrm{X}_z + \Theta . \overline{\mathrm{M}_z} + \mathrm{D}_t + \mathrm{D}_{d,j} + \varepsilon_{z,j} \qquad (4)$$

$\text{Ln}\ \mathrm{P}_{z,j}$ is the natural logarithm of the price (first or second price record) of a commodity-unit pair *j*, and CON_z the connectivity variable in EA *z*. Standard errors are robust to heteroskedasticity and are clustered at the EA level. X_z is a set of EA-level controls (Appendix A.6). $\overline{\mathrm{M}_z}$ is a set of HH-level controls, averaged at the EA level, that encompasses head of HH characteristics, HH demographics, housing, living standards, and exposure to shocks (Appendix A.5 and A.8). The equation is estimated by 2SLS but OLS estimates are reported in Appendix B.2.1.

Initially, the analysis is conducted on the price levels (records 1 and 2) of commodity-unit pairs most commonly traded in EAs.[12] We introduce FEs for each district commodity-measurement unit combination, $\mathrm{D}_{d,j}$, to capture district-level intrinsic price differences between different commodity-measurement unit pairs, as well as difference in prices potentially induced by weight gaps observed for the same commodity-unit pair traded in different districts. This calibration thus makes it possible to analyze the effect of digitalization, and more specifically of connectivity at the EA level, on the general level of commodity prices. Overfitting concerns are addressed through alternative FEs and control variables calibrations in Appendix B.2.3.

2. Digitalization and price levels

Table IV presents results of 2SLS estimations of equation (4). Appendix B.2.1 reports OLS estimates, Appendix B.2.2 reports associated control estimates of 2SLS estimations, while Appendix B.2.3 provides 2SLS estimates with alternative calibrations of FEs in the model. The first-stage statistics suggest that the risk of bias resulting from a weak instrument is limited: the Kleibergen-Paap (KP) Wald statistics largely exceed 10[13], the Anderson-Rubin test rejects the hypothesis of instrument invalidity within a 99% confidence interval, and the KP under-identification test rejects the hypothesis of under-identification within a 95% confidence interval. Estimates

[12] For each commodity, we have retained the unit of measurement most commonly traded in the WAEMU's EAs. We ranked these commodity-unit pairs by the number of EAs trading them in the zone Appendix A.4 details and ranks each pair in descending order according to the number of EAs per country trading them.

[13] The general rule of imposing an F-test KP greater than 10 to ensure instrument strength has since been challenged, with the Anderson-Rubin test (with one instrument) being preferred (Andrews et al., 2019; Keane & Neal, 2023).

provided in Appendix B.2.3 are consistent across model calibrations, suggesting that district-product FEs inclusion do not lead to overfitting bias.[14]

According to 2SLS estimates, a 1% reduction in the distance of EAs from the network increases the general level of food prices by 0.04% (columns (1) and (4)). To make the interpretation of these number easier, the estimates made with the proximity dummies (columns (2) and (3)) suggest that the deployment of mobile cell towers within 2 km or 5 km of an EA's centroid increases the general level of food prices within these EAs by around 10-12%. These estimates are in line with various studies on this subject using similar connectivity measures, which tends to confirm their relevance.[15] Marginal effects of network connectivity on the price level of the most-traded products are reported in Appendix D.2.4. Of these 13 products, four saw their price significantly affected by connectivity: the price of salt (small bag) increased by 34%, fresh okra (small heap) and chili pepper (small heap) by 43% and 52% respectively, while the price of beef (1 kg) diminished by 18%. Thus, while an increase in the average price level of commodities in connected areas was observed, the effect of connectivity was nevertheless heterogeneous according to the type of commodity considered.

[14] Estimates of average prices increase vary between from +6% to +12%. In particular, 2SLS-estimation of equation (4) with product-unit FEs only and without control variables yields the same estimate as 2SLS-estimations with district-product-unit and survey wave FEs and control variables, that is, a 11-12% increase in food prices.

[15] Studies conducted in Ghana, have also found that access to ICT increases maize prices by 10%, groundnut prices by 7% (Courtois & Subervie, 2015), and yam prices by 9% (Soldani et al., 2023). Outside west Africa, Svensson and Yanagizawa (2009) highlight a 15% increase in the sales price of maize following access to ICT in Uganda. Nakasone (2013) highlights an 11%-13% increase in the general level of agricultural commodity prices in Peru. In India, Goyal (2010) find that the deployment of internet kiosk and warehouses, providing wholesale price information, has led to a 1–3 percent increase in soy price, concomitant to a decrease in price dispersion. See Aker and Cariolle (2023) for a recent review of these studies.

TABLE IV. EQUATION (4), 2SLS ESTIMATIONS.

Dep. Var : Ln $P_{z\,i}$	(1)	(2)	(3)	(4)	(5)	(6)
	2nd stage estimates					
	Price record 1			Price record 2		
Distance 2G+ (ln, km)	-0.037***			-0.039***		
	(0.011)			(0.011)		
Dist. 2G+ <2km (0/1)		0.111***			0.118***	
		(0.035)			(0.034)	
Dist. 2G+ <5km (0/1)			0.103***			0.110***
			(0.032)			(0.032)
Controls (X_z; $\overline{X_m}$)	Yes	Yes	Yes	Yes	Yes	Yes
District-prod. FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,740	129,670	129,687	129,738	129,668	129,685
AR F-test (p-val.)	0.000749	0.000802	0.000742	0.000254	0.000271	0.000252
KP Wald F-stat	67.23	47.24	65.34	67.23	47.24	65.34
KP rank LM-stat	47.52	31.70	29.50	47.52	31.70	29.50

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

3. Digitalization and price convergence

The heterogeneous effect of connectivity on prices can be explained by the spatial rebalancing of food supply and demand between urban and rural areas. We explore this possibility by augmenting the basic econometric model with an interaction term between the connectivity variable (CON_z) and urban location (URB_z).

$$\text{Ln } P_{z,j} = \gamma_0 + \gamma_1 . CON_z + \gamma_2 . CON_z \times URB_z + \gamma_3 . URB_z + \Gamma . X_z + \Theta . \overline{M_z} + D_{d(j)} + D_t + \omega_{z,j} \qquad (5)$$

URB_z is a variable taking the value of 1 if the EA is an urban area, 0 otherwise. We instrument the connectivity variable and the interaction term by the instrument ($Lightning\_risk_z$) alone and also the interaction between the instrument and the urban area dummy variable ($Lightning\_risk_z$ x URB_z).

The results are reported in Table V. The first-stage statistics confirm the validity of the instrument set. Results conducted on non-converted product prices highlight the spatially heterogeneous effects of connectivity and support the hypothesis of food prices convergence between urban and rural areas, driven by price-level catch-up in rural areas. Indeed, estimates show that proximity to mobile network towers significantly increases the general level of food prices in rural areas, while its effect is substantially weaker in urban areas.

Then, we set the analysis of spatial price convergence at the district level, and address the impact of 2G+ network coverage, expressed as a share of the district area, on the coefficient of variation in food price levels. Such analysis has to be conducted at the district level, since prices are observed at EA level.

$$\mathrm{CV_{d,j}} = \delta_0 + \delta_1.\mathrm{CON}_d + \Gamma.\overline{\mathrm{X}_d} + \Theta.\overline{\mathrm{M}_d} + \mathrm{D_{r,j}} + \omega_{\mathrm{d,j}} \quad (6)$$

$\mathrm{CV_{d,j}}$ is the coefficient of variation of the price of food commodity j observed in the EAs, calculated at the district level d. $\overline{\mathrm{X_d}}$ is a set of EA-level controls, averaged at the district level, excluding EA's topography variables (Appendix A.6). $\overline{\mathrm{M}_d}$ is the set of HH-level control variables, averaged at the district level, that encompasses head of HH's characteristics, HH's demographics, housing, living standards, and exposure to shocks (Appendix A.5 and A.8). $\mathrm{D_{r,j,u}}$ is a region-commodity-unit fixed effect, to control for unobservable heterogeneity of regions and commodity-unit pairs traded within them. ω_d is an error term. Standard errors are robust to heteroskedasticity and clustered at the commodity-region level.

Results in column (1) of Table VI do not allow us to conclude that mobile coverage has a significant effect on price dispersion. However, the Anderson-Rubin test points to the weakness of our instrument. It is possible that weighting the number of lightning strikes by population density is relevant for a disaggregated level of analysis such as EAs, but this relevance disappears at a more aggregated level such as districts, with possible heterogeneous population densities.

For this reason, we re-estimate equation (6) using the simple (unweighted) average number of lightning strikes observed at the district level (column (2) and (3)). In columns (4) and (5), we additionally control for the averaged product price level, to account for a potential nonlinear relationship between price dispersion depending on price levels. In this case, network coverage could affect price dispersion through its effect on average price levels, evidenced in previous subsections.

First-stage statistics confirm the validity of the unweighted instrument, and the second-stage estimation highlights a negative and significant effect of mobile network coverage on commodity price dispersion at $p < 0.05$. According to our estimates, a 10% increase in network coverage leads on average to a 5% decrease in the coefficient of variation of commodity prices. These estimates are not sensitive to the inclusion of food-product price level, even if the latter has a positive and 1%-significant effect on price dispersion.

TABLE V. EQUATION (5), 2SLS ESTIMATIONS.

Dependent variable: Ln $P_{z\,i}$	(1)	(2)	(3)	(4)	(5)	(6)
	2nd stage estimates					
	Price record 1			Price record 2		
Distance 2G+ (ln, km)	-0.050***			-0.051***		
	(0.012)			(0.011)		
Distance 2G+ × urban (0/1)	0.046**			0.040*		
	(0.020)			(0.020)		
Distance 2G+ <2km (0/1)		0.152***			0.154***	
		(0.039)			(0.038)	
Distance 2G+ <2km × urban (0/1)		-0.119***			-0.106**	
		(0.046)			(0.047)	
Distance 2G+ <5km (0/1)			0.139***			0.140***
			(0.035)			(0.034)
Distance 2G+ <5km × urban (0/1)			-0.121**			-0.104*
			(0.060)			(0.061)
Controls (X_z; $\overline{X_m}$)	Yes	Yes	Yes	Yes	Yes	Yes
District-prod. FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,740	129,670	129,687	129,738	129,668	129,685
AR F-test (p-val.)	3.42e-05	3.84e-05	3.23e-05	1.11e-05	1.25e-05	1.05e-05
KP Wald F-stat	11.28	23.78	10.22	11.28	23.78	10.22
KP rank LM-stat	12.84	37.73	7.637	12.84	37.73	7.645

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

TABLE VI. EQUATION (6), 2SLS ESTIMATIONS.

Dep. var: CV_{dju}	(1)	(2)	(3)	(4)	(5)
	2nd stage estimates				
Price record:	Record 1		Record 2	Record 1	Record 2
2G+ coverage (%)	0.038	-0.518**	-0.510**	-0.524**	-0.515**
	(0.400)	(0.205)	(0.205)	(0.205)	(0.205)
Ln $P_{d,j}$				0.000***	0.000***
				(0.000)	(0.000)
IV:	Baseline (weighted)	Unweighted			
Controls	Yes	Yes	Yes	Yes	Yes
Region-prod. FE	Yes	Yes	Yes	Yes	Yes
Observations	19,399	19,399	19,399	19,399	19,399
AR F-test (p-val.)	0.924	0.00598	0.00694	0.00518	0.00603
KP Wald F-stat	32.66	41.82	41.82	41.77	41.76
KP rank LM-stat	54.72	41.51	41.51	41.47	41.46

Standard errors in brackets, robust to heteroskedasticity and clustered by region-product. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

4. The demand-channel

While the supply channel has been widely investigated in the literature, the role of demand in explaining price dynamics has been often overlooked. However, the rise in the general level of food prices and the spatial convergence of prices can be explained by increased demand, particularly in rural areas, since HHs are often both suppliers and buyers on food markets. Digitalization, by fostering agricultural productivity, financial inclusion, or by improving HH access to the labor market and off-farm income sources, can lead to an increase in HH purchasing power, and thus an increase in the demand for food products. However, increased food demand may also be the result of higher farm revenue accruing to higher agricultural commodity prices.

To disentangle these mechanisms, we test the demand channel by first including in equation (4) the interaction term between the distance to the mobile network and total food spending (XOF, ln) extrapolated at the EA level[16]. We also control additively by including imputed total food and non-food spending variables. Results are presented in Table VII below. Estimates support the relevance of the demand channel, since the interaction between network proximity and food spending is positive and significant at the 1% level, while standalone spending variables are either negative or null. Then, we control in columns (5) and (6) for extrapolated total farm sales in EAs[17], to ensure that estimated demand-effect does not result from reverse causality, that is, higher food price generating higher farm revenues and thereby higher food purchases, or higher prices inducing food supply reallocation.

The magnitude and significance of our estimates are not altered by the inclusion of this variable, thereby supporting the relevance of the demand channel to explain food-price catchup in rural areas. Following up on this evidence, the next subsection further addresses the impact of digitalization on HH demand for food products.

[16] We compute spending per capita by averaging spending (XOF) by HH member at the EA level, multiplying the result by the EA population size, and then transforming it in logarithm.

[17] In the same spirit as EA spending, we first compute HH's total farm sales (XOF) by summing HH sales by product, divide the result by HH size, average it at the EA level, multiply it by the EA population size, and finally transform it in logarithm.

TABLE VII. NETWORK CONNECTIVITY AND THE DEMAND CHANNEL

Dep. var: $P_{z\,i}$ (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)
Price record:	1	2	1	2	1	2
Network variable:	Distance (km, ln)		Distance 2G+ <2km (0/1)			
Network	0.131**	0.149**	-0.424**	-0.476**	-0.572*	-0.567*
	(0.061)	(0.064)	(0.185)	(0.192)	(0.297)	(0.305)
Network × EA food spend.	-0.008***	-0.009***	0.026***	0.029***	0.033**	0.033**
	(0.003)	(0.003)	(0.010)	(0.010)	(0.015)	(0.016)
EA food spend. (XOF, ln)	-0.000	-0.001	-0.014	-0.020**	-0.006	-0.011
	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
EA non-food spend. (XOF, ln)	0.000	0.000	-0.001	-0.001	-0.002	-0.008
	(0.007)	(0.007)	(0.008)	(0.007)	(0.009)	(0.009)
EA farm sales (XOF, ln)					0.001**	0.001*
					(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
District-prod. FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,738	129,738	129,670	129,668	97,088	97,086
AR F-test (p-val)	0.000185	8.53e-05	0.00033	8.31e-05	0.00688	0.00232
KP Wald F-stat	67.12	32.11	24.56	24.56	20.73	20.73
KP rank LM-stat	47.29	49.38	31.35	31.35	27.21	27.21

Standard errors in brackets, robust to heteroscedasticity and clustered by district. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

B. Mobile connectivity and HH demand for food products

The following analysis of the effects of digitalization on food demand is carried out at the household level, focusing on the quantities of food commodities consumed and purchased. We are also interested in the effect of digitalization on total household spending on both food and non-food products, particularly in rural areas. Based on the literature on mobile phone diffusion in rural areas of low-income countries (Aker & Mbiti, 2010; Abate et al, 2023; Aker & Cariolle, 2023), we focus on HH mobile phone adoption, leaving the analysis of internet adoption for the section on robustness checks.

1. Model and hypothesis testing

In this section, we examine the relationship between mobile connectivity and HH food spending, as well as quantities of food products both consumed and purchased by the HHs. We assume that better access to market information via mobile technologies will directly facilitate the purchase of a greater quantity of food products. Indirectly, digitalization generates improvements in HH living conditions (notably income), which are expected to boost the quantity of commodities consumed and purchased, hence lowering their reliance on self-consumption.

Since the analysis is conducted at the household level m, or of product j consumed/purchased by this household, we are interested in the combined effect of connectivity in the EAs (CON_z) and adoption of mobile technologies (AD_m), on HH (food) expenditures, and finally on the quantity of food commodities (self-)consumed or purchased by these households ($DEM_{m(j)}$). We then estimate the following equation:

$$DEM_{m(j)} = \delta_0 + \delta_1 . CON_z \times AD_m + \delta_2 . AD_m + \Gamma . M_m + D_z + D_t(+D_j + D_k) + \omega_{m(j)} \quad (7)$$

Where the interaction term ($CON_z \times AD_m$) is instrumented by our initial instrument interacted with the number of cell phones in the household m (AD_m).[18] CON_z is the distance variable (km, log) or a dummy for the proximity to the nearest 2G, 3G or 4G tower. M_z is the set of baseline HH control variables. Therefore, $DEM_{m(j)}$ is by sequencing order either[19]:

i) a set of expenditure variables – total, food and non-food – (in XOF, transformed into logarithms) per HH member.
ii) the quantity (in log-transformed grams) of a commodity (self-)consumed per HH member,
iii) the quantity (in log-transformed grams) of a commodity purchased per HH member.

Variable definitions and descriptive statistics are provided in Appendix A. X_m is a set of control variables for the household characteristics discussed in section A.3. $\omega_{m(j)}$ is an error term. In addition to baseline control variables, we include control variables for mobile telephone adoption (AD_m) additively, and a dummy for internet access in the home or outside the home.

When we look at total household expenditure on food and non-food items, we use the initial set of control variables and include survey wave and EA FEs. We again test of alternative model calibrations to prevent possible overfitting bias. When investigating the quantities of commodities consumed or purchased, we add the diversity of commodities consumed to the initial set of controls[20], and include FEs for EAs, survey waves, commodity-measurement units (D_z, D_t, and D_j).

Interacting the instrumented network connectivity with a digital technology adoption variable could lead to bias arising from the simultaneous relationship between digital technology adoption and food products demand. This bias should be limited, but not fully ruled out, by additively controlling for mobile and internet adoption by HHs,

[18] The instrument interacts as follows: $IV_m = Lightning\_risk_z \times AD_m$.

[19] Food diversity, proxied by the number of (self-)consumed products, is also addressed in Appendix B.5.

[20] Removing this additional control does not change the results.

which is expected to account for the unconditional nexus between digitalization and food consumption, and also by the large range of household characteristics (Appendix A.4) which could both explain digitalization and food consumption.[21]

2. Digitalization and household spending

First, we start this sub-section with an analysis of the effect of digitalization on HH food spending. We estimate equation (7) using food expenditure per HH member (in log-transformed XOF) as the dependent variable, and additionally controlling for non-food spending.[22] Estimations using total and non-food expenditures per HH member are also conducted (see Appendix B.4.1 and B.4.2 respectively). Results are reported in Table VIII. To ensure the model is not overfitted by the inclusion of EA FEs, we also run estimations of equation (7) by instrumenting together network proximity alone and network connectivity interacted with mobile phone ownership, excluding FEs and baseline control variables (column (3)).[23] Then, we progressively add to the model HH control variables (column (4)), EA control variables previously used in Section III.A (column (5)), and finally district and survey wave FEs (column (6)).

Estimations show a positive and significant effect of mobile connectivity on food spending. Estimates are also poorly affected by omitted variable bias and are not overfitted by the inclusion of EA FEs, as suggested by the various model calibrations reported in columns (3) to (6). More conservative estimates stress that the acquisition of a telephone by a households located within 2 km of a mobile tower contributes to a 13%-increase in food expenditure (column (2)). Interestingly, estimates of the standalone connectivity variable (variable (C)) included in estimations reported in columns (3) to (6) show that improved network coverage reduces food spending of HHs who do not own mobile phones, suggesting the presence of a negative externality that could be related to rising food prices evidenced in the previous section. Moreover, estimations conducted on urban and rural sub-samples (columns (7) and (8)) show that this effect is stronger in rural areas, where mobile connectivity contributes to a 37.5% increase in food spending, compared to an 11% increase in urban areas. Additional estimations presented in Appendix B.4.1 confirm these spending patterns for total expenditures – 63.7% increase in rural areas compared to 12.5% in urban areas – and non-food expenditures – 34% increase in rural areas only, with no effect observed for urban areas.

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[21] Reduced form estimations, conducted in the robustness section IV.D, suggest that the IV exclusion restriction is respected.

[22] Removing this additional control does not the significance of estimates, only their magnitude.

[23] But controlling for the number of mobile phones in the HH (interaction variable), internet access, and HH non-food spending (XOF, ln). Excluding this latter variable does change the significance and sign of the estimated effect, but increases its magnitude.

Importantly, consumption patterns are not altered by the inclusion of total HH farm sales as a control, despite sample attrition that occurs when this variable is included (Appendix B.4.3). This last piece of evidence suggests that this demand-side effect is not driven by increased farm revenue accruing to higher food-product prices. Overall, it seems likely that the increased food demand from (rural) households digitalized and located close to the mobile internet network is a factor explaining the rise in prices in connected (rural) areas.

TABLE VIII. MOBILE CONNECTIVITY AND FOOD EXPENDITURE PER HH MEMBER, 2SLS ESTIMATES.

Dep. Var.: food spending per cap. (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6) Urban	(7) Rural
(A) Dist. 2G+ <2km (0/1)	0.128***	0.109**	0.074**	0.084**	0.117***	0.110**	0.375***
× # mob.	(0.030)	(0.044)	(0.033)	(0.034)	(0.031)	(0.048)	(0.145)
(B) Dist. 2G+ <2km (0/1)	-	-0.865***	-0.518***	-0.422**	-0.289**	-	-
	-	(0.228)	(0.120)	(0.165)	(0.138)	-	-
HH controls	Yes	No	Yes	Yes	Yes	Yes	Yes
EA controls	No	No	No	Yes	Yes	No	No
EA FEs	Yes	No	No	No	No	Yes	Yes
District FEs	No	No	No	No	Yes	No	No
Survey wave FEs	Yes	No	No	No	Yes	Yes	Yes
Observations	56,817	56,819	56,817	55,466	55,466	23,220	33,597
AR F-test (p-val.)	1.22e-05	6.04e-10	5.11e-07	0.0133	0.000148	0.0321	7.03e-05
KP Wald F-stat	102.2	16.48	41.86	15.74	14.57	47.68	12.13
KP rank LM-stat	67.63	23.20	63.98	20.59	20.10	21.33	9.804

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01. In columns (3) to (6), (B) and (C) are instrumented by the lightning strike IV and the lightning strike IV interacted with the number of mobile phones in the HH. All estimations include the number of mobile phones, internet access (0/1), and non-food spending (XOF, ln) as control variables.

3. Digitalization and (self-)consumption of food commodities

Thirdly, we estimate equation (7) using the quantity of food products consumed per HH member as the dependent variable. Results reported in Table IX highlight a positive and significant effect of HH mobile connectivity on food consumption (columns (1) and (2)), again more marked in rural areas (columns (5) and (6)) than in urban ones (columns (3) and (4)). According to these estimates, HH mobile connectivity contributes to a 20% increase in food consumption quantity, 23% in urban areas compared to 41% in rural areas. By contrast, better mobile connectivity reduces the quantity of self-consumed food per HH member (-9%), especially in rural areas (-19%) (columns (7) to (12)). Supplementary analysis conducted in Appendix B.5 show that HHs consume a greater variety of food products while lowering the number of self-consumed items. So, it seems that mobile phone adopters, in particular rural HHs, are able to consume a greater quantity and variety of food products while reducing their self-consumption.

In Appendix B.6, we also report the marginal effects of mobile connectivity on the quantities consumed of each of the 15 commodities most consumed by households in at least 7 WAEMU states. The results show an overall significant and positive effect on the quantities of commodities consumed, with the exception of tea (negative effect, significant at 10%), red and refined palm oils, fresh okra and imported rice (non-significant effect). We observe a marked positive impact for peanut oil, salt, sugar, fermented locust bean, coffee, and bouillon cubes.

Thirdly, we look at the effect of digitalization on the quantities of products purchased by HHs. We therefore re-estimate equation (7), using the quantity of food purchased per HH member as the dependent variable. We highlight a positive and significant effect of mobile connectivity on the quantity of food purchased, in both rural and urban areas. According to our estimates presented in Appendix B.7, mobile phone acquisition by a household located less than 2 km from a mobile network tower contributes to a 26% increase in the quantity of food purchased, with a 29% increase in urban areas and a 55% increase in rural areas.

In sum, digitalization therefore appears to be an important driver of improving living conditions, and thereby, of the catchup in food prices that was observed in rural areas. However, results highlight a negative externality of mobile connectivity on HHs located in connected areas but with a low level of digitalization, since the latter suffer from the increase in the general level of food prices without benefiting from the increase in purchasing power associated with digitalization.

TABLE IX. MOBILE CONNECTIVITY AND QUANTITY OF COMMODITIES CONSUMED PER HH MEMBER, 2SLS ESTIMATES.

Dep. Var.: quantities consumed per cap. (grams, ln)	(1)	(2)	(3)	(4)	(5)	(6)
			Urban		Rural	
Distance 2G+ (ln, km) x # mob.	-0.077***		-0.088***		-0.185***	
	(0.009)		(0.016)		(0.042)	
Distance 2G+ <2km (0/1) x # mob.		0.196***		0.226***		0.406***
		(0.023)		(0.042)		(0.075)
Observations	950,617	950,458	480,658	480,658	469,533	469,374
Anderson-Rub. F-test (p-val.)	0	0	4.07e-07	4.07e-07	0	0
KP Wald F-stat	236.6	323.4	114	153.1	30.97	59.07
KP rank LM-stat	190.7	212	106.5	91	28.09	47.33
Dep. Var.: quantities self-consumed per cap. (grams, ln)	(7)	(8)	(9)	(10)	(11)	(12)
			Urban		Rural	
Distance 2G+ (ln, km) x # mob.	0.035***		0.028*		0.098*	
	(0.011)		(0.016)		(0.050)	
Distance 2G+ <2km (0/1) x # mob.		-0.088***		-0.073*		-0.186**
		(0.027)		(0.042)		(0.088)
Observations	1,153,952	1,153,711	555,821	555,821	597,594	597,352
Anderson-Rub. F-test (p-val.)	0.00143	0.00143	0.0727	0.0727	0.0308	0.0310
KP Wald F-stat	231.2	318.3	111.7	153.4	14.23	36.71
KP rank LM-stat	187.4	215	100.3	86.37	13.35	31.21
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Product-unit FEs	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in brackets, robust to heteroskedasticity and clustered by HH. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

IV. ADDITIONAL EVIDENCE

In this section, we explore the contribution of mobile-enabled services, i.e. internet access and mobile money, as well as income diversification and entrepreneurship, in explaining demand and food price patterns.

A. Mobile-enabled services

1. Internet access

Since mobile phones are the principal engine for internet access, it is possible that estimated effects of mobile connectivity rely on internet-based technologies, rather than feature phone technologies, such as communicating with other agricultural market actors or receiving tailored agricultural extension advice by video (Ayalew et al., 2022; Abate et al., 2023b). To test the moderating effect of internet access, we re-estimate equation (7) by interacting the network connectivity variable with the internet adoption dummy, also which was until now additively included as a control (Appendix D.1). Overall, the impact of internet access, despite being consistent with estimated effects of mobile phone access in general, is more moderate and less clear-cut, probably due to its high cost and a lower absorption capacity of internet-based technologies by populations, particularly rural ones. Similar evidence is obtained when restricting the EA's distance variable to 3G and 4G networks only. We therefore conclude that the impacts and mechanisms presented in previous sections of this manuscript are mainly explained by simple mobile phone connectivity.

2. Financial inclusion

Another plausible channel for the effect of mobile connectivity on food demand is financial inclusion, especially through the deployment of mobile money (MM) systems (Aker et al., 2016). MM allows for the easy transfer of funds within countries and from abroad. Transfers sent to family members in rural areas can be used to purchase food, invest in agricultural activities, or start small food-related businesses. Furthermore, the ability to make digital payments reduces the need for physical cash, making transactions safer and more convenient, especially in remote areas.

We test the role of MM as mediator and moderator, by first adding as controls into equation (7) dummies indicating whether HHs possesses a MM account, a standard bank account, or a microfinance/rural saving bank account, which are the main mediums of HH financial inclusion in the LSMS sample (Appendix D.2.1). If MM moderates the effect of mobile connectivity, estimates associated with mobile connectivity should be sensitive to the inclusion of the MM account dummy, while not being sensitive to the inclusion of the other financial account dummies. This is what we observe in columns (1) to (3) in Appendix D.2.2, as the estimated effect of mobile connectivity on total spending evidenced in Appendix B.4.1 (column (2)) is lowered by the inclusion of the MM account dummy, while not being affected by other financial variables.

We then estimate the contribution of MM adoption to total spending in column (4) by replacing the mobile connectivity variable with a MM access-connectivity variable, which was obtained by multiplying together the dummy variable for 2 km-proximity to a 2G+ network and the dummy variable for owning a MM account, and instrumenting this new variable by our IV interacted with the MM dummy. We also include and instrument both the mobile connectivity and MM connectivity variables in column (5), to identify the respective contribution of mobile phone and mobile money account ownerships' contribution to HH spending. Results support that mobile money account ownership is a separate and significant channel through which mobile connectivity increases HH spending. Mobile connectivity remains positive and significant, suggesting that other mechanisms are at play. Next, in columns (6) to (11), we rerun the same estimations using the food and non-food expenditure variables, and splitting the sample between urban and rural HHs, and find that the mobile money channel is relevant to explaining food expenditures only, with a stronger effect for rural HHs.

Finally, we estimate the effect of MM connectivity on food demand, using the quantities of (self-) consumed commodities, as well as the quantities of commodities purchased, as dependent variables. Results, reported in Appendix D.2.3 to D.2.6, show that MM connectivity is found to increase the quantities of food consumed and purchased, especially by rural HHs. The effect on self-consumption is not significant, except for connected rural HHs, who experienced a 10%-significant decrease in self-consumed quantities. Overall, this evidence suggests that MM is therefore a mobile-enabled technology that has likely contributed to food price catch-up in rural areas and reduced food price dispersion, through its effect on food product consumption and purchase.

B. On-farm, off-farm revenues and non-agricultural entrepreneurship

In this subsection, we explore the effect of mobile connectivity on HH income source diversification and entrepreneurship (JOB_m). Income diversification is proxied by the share of HH members involved in on-farm and off-farm revenue-generating activities[24], while entrepreneurship is measured by the number of non-agricultural enterprises created within the HH. The following model is estimated:

$$JOB_m = \delta_0 + \delta_1 . CON_z \times AD_m + \delta_2 . AD_m + \Gamma . M_m + D_z + D_t + \omega_m \qquad (8)$$

When JOB_m is the HH entrepreneurship variable, we additionally control for the time passed since the first enterprise created within the HH.[25] Results, reported in Appendix D.3.1, show mobile connectivity respectively increases by 9% and 6% the share of HH members earning off-farm and on-farm incomes, respectively, suggesting that connectivity increases the share of HH members engaged in revenue generating activity. The difference in the magnitude of the coefficient also stresses that income diversification is promoted through off-farm activities. Moreover, these effects are stronger for rural HHs (+27%; +17%) compared to urban ones. Estimations conducted on the number of non-agricultural enterprises are reported in Appendix D.3.2 and support that mobile connectivity also contributed to non-agricultural entrepreneurship (column (1)), especially in rural areas (column (3)). Overall, this last piece of evidence supports the hypothesis that the effect of connectivity on food demand and food price convergence has likely been triggered by improved access to off-farm and non-agricultural revenues in rural areas.

[24] A HH member is considered to be engaged in on-farm activity if she/he worked at least one hour in a farming on her/his own benefits during the 7 days preceding the survey. A HH member is considered to be engaged in off-farm activity if she/he carried out at least one paid hour for her/his own business, for the public sector or as an apprentice, during the 7 days preceding the survey.

[25] Results remain robust to this control variable exclusion.

V. ROBUSTNESS CHECKS

A. Converted commodity prices

First, we check the robustness of the estimated price impact of digitalization by converting food-product prices in XOF per gram using measurement-unit conversion factors. This approach enables the price comparison of different measurement units of a given product, and thereby limits the sample attrition caused by our baseline approach, consisting in focusing on the most traded product-unit pairs. However, it comes at the risk of introducing statistical noise induced by potential inaccuracies in reported unit conversion factors.

The resulting dataset therefore associates product-unit pair to its corresponding price per gram. Estimations of equations (4) to (6) are conducted using converted prices. Estimates reported in Appendix E.1, are consistent with baseline estimations, albeit slightly less significant, suggesting possible measurement errors induced by the application of unit conversion factors.

B. Mobile network quality

Second, our connectivity measure, based on distance to cell towers as reported in the OCI database, may be an imprecise measure of true network quality in a given community. HHs located close to the network may suffer from poor connectivity because of adverse geographic conditions, poorly maintained cell towers (considering that most cell towers in rural areas are powered by off-grid generators), and disruptions in access to mobile internet connectivity. Cell tower locations may also be imprecisely reported in the OCI database. Moreover, the EAs in the LSMS database exhibit a wide range in total land area, meaning that the distance from the centroid of a given EA to the closest cell tower may reflect varying actual distance to a cell tower, and hence varying network quality. Last, this measure does not provide information on the extent of mobile network availability: in many cases, only one specific operator may own the last mile infrastructure, leaving limited (when there are inter-operability agreements) to no capacity for other mobile operators to reach populations.

To circumvent this limitation, we augment previous measures of network connectivity by combining survey data on the number of well-captured mobile networks in each EA. Thence, we construct the following mobile network variables:

- A dummy equal to one if at least one mobile network is well-captured within 2km from the closest cell tower.
- A dummy equal to one if at least two mobile networks are well-captured within 2km from the closest cell tower.
- A dummy equal to one if at least three mobile networks are well-captured within 2km from the closest cell tower.

- The number of mobile networks well-captured within 2km from the closest cell tower.

Baseline estimations on the effect of network connectivity on food product prices and of mobile connectivity on HH quantities of consumed food products are reported in Appendix E.2.[26] They confirm the robustness of our results and show that greater network quality accentuates the impact of mobile connectivity on food markets and rural livelihoods.

C. Sensitivity and instrument validity tests

1. Spatial anonymization

Third, spatially anonymized datasets such as the LSMS may lead to measurement errors due to privacy protection methods, consisting of randomly offsetting true EA coordinates by zero to two kilometres (km) in urban areas, and two to five km in rural areas, with an additional small percentage of EAs offset one to ten km (Michler et al., 2022). The combination of geolocated survey data with remote sensing data such as lightning strikes recorded in the VHRFC dataset could therefore generate biased estimations. To address this potential issue, we follow Michler et al (2022) in adopting bilinear and polygonal extraction approaches, described in Appendix E.3.1, to count lightning strikes and to build our instrumental variable. Results, reported in Appendixes E.3.2 and E.3.3 are robust to this first sensitivity test.

2. Reduced-form estimations

Fourth, we proceed to reduced-form estimations, where the dependent variable is successively the various agricultural outcomes emphasized in equations (4) to (7) and the regressor is the instrument. If the instrument is not correlated with the residuals, it should be significant and its effects on dependent variables should be consistent with that of instrumented variables. Estimates, reported in Appendix E.4.1 and E.4.2, have the expected sign and confidence level. We also pay attention to a possible direct effect of the IV on prices tied to population density in reduced-form estimations of equation (4) reported in Appendix E.4.1. Density and IV estimates remain stable across estimations suggesting that they do not suffer from this source of bias.

3. The exclusion restriction assumption

Fifth, we also test a possible direct effect of lightning risk on outcome variables, explained for instance by total rainfall, lightning-related power outages, or fires. One particular possibility is that bias induced by rainfall can adversely affect crops as well

[26] For the sake of results conciseness, results with the other HH-level outcome variables are not reported. They can be provided upon request.

as movement of people and goods. It is also a predictor of current lightning activity, which could induce power outages in some locations (Mensah, 2024). Moreover, our variable of structural exposure to lightning activity could also be associated with long-term exposure to higher overall rainfall, which in turn could directly favor agricultural development. In Appendix E.5.1, we therefore estimate baseline equation (4), additionally controlling for daily rainfall within the EAs averaged over 2018 or 2019 (columns (1) and (2)), and for lagged rainfall precipitation averaged over 2017 (columns (3) and (4)), or over the period 2015-2019 (column (5) to (8)). Results show that first and second-stage estimates remain unaffected by the inclusion of both current and/or past rainfall variables.

Moreover, we provide a more general test of a possible direct effect of the IV on spending in EAs, by regressing EA-level spending variables, used in Section III.4, over the instrument and population density (columns (1) to (3)), and then including our connectivity variable – i.e. the EA distance to the nearest cell tower – as a control (columns (4) to (6)). Results in Appendix E.5.2 show a negative and significant effect of lightning strikes on spending variables, which becomes positive and non-significant once distance to the nearest cell tower is included in the model. By contrast, this latter variable is found to have a negative and significant effect on spending, therefore suggesting that the previous negative effect of lightning activity on spending passes through reduced mobile network connectivity. We adopt the same approach using EA-level farm sales as the dependent variable in Appendix E.5.3. We observe a similar reversal in the sign of the IV coefficient, and a similar transfer in significance between the IV and the network distance variable, after including the latter in the model. Overall, these tests support that the exclusion restriction is well-respected.

4. Network externality, mobile spillovers and the SUTVA

Sixth, the SUTVA would be violated if the response of a particular HH would be affected by proximate HHs' response to improved connectivity, or if adoption of a mobile phone by a HH would deteriorate proximate non-adopters' livelihood. To rule out this possibility, we need to control for economic externalities resulting from improved connectivity as well as digital spillovers resulting from the diffusion of mobile phones in the community. Replacing EA-level by district-level FEs, we identify network externalities by adding the (non-interacted) network proximity dummy in equation (7), as already done in Appendixes B.2.3 and B.4. Additionally, we control for mobile spillover effects on non-adopters and adopters, by respectively including the share of HH owning mobile phones in the EA and the interaction between this share and the number of mobile phones in the HH. We run estimations using the HH food spending and food consumption per capita as dependent variables, and report estimates in Appendix E.6.1.

Results show that the effect of mobile ownership in connected areas (line (A)) is robust to controlling for digital spillovers (lines (C) and (D) and relatively stable across estimations. They also confirm that HH without mobile phones in connected EAs also face a negative externality, as network proximity is associated with a 30% decrease in the latter's food expenditures and a 17% decrease in their quantities of food consumed, which could be explained by the rising food costs previously evidenced (line (B)). Taken together, estimates suggest that the negative network externality on HH food demand is overcome once households own at least two mobile phones, which is approximately the sample average (Appendix A.3.1).

5. Sensitivity to individual country exclusion

Last, we conduct sensitivity tests by estimating equation (4) and removing each WEAMU member state one by one. Resulting estimates and confidence level are portrayed in Appendix E.6.2. Estimates remain robust and stable after each country exclusion, except with the exclusion of Côte d'Ivoire. Removing this country leads to an estimated effect similar in magnitude to other estimates, with however a loss in significance. This result can be explained by the large share of Ivoirian EAs in the total sample (22%). It can also find an explanation in the IV's loss in strength resulting from its spatial distribution, concentrated in Côte d'Ivoire. Nevertheless, the instrument regains strength and the estimated effect gets back to an acceptable significance level when levelling-up the FEs to the region-product level and double-clustering standard errors by country and product-unit to exploit higher-level variability in instrumental and instrumented variables.

VI. CONCLUDING REMARKS

This study offers a larger perspective on how connectivity infrastructure and the adoption of mobile technologies are transforming rural livelihood in WAEMU member states. The analysis addresses critical and interdependent aspects of food market functioning, including price levels and dispersion, household food spending and consumption patterns, as well as access to agricultural and non-agricultural sources of income.

This paper shows that improved mobile network coverage leads to food price convergence, driven by connectivity in rural areas. Without dismissing the relevance of supply-driven mechanisms, our analysis differs from other analyses found in the literature in that it investigates the salience of the demand channel. In fact, it explains observed food price patterns by the increased demand for food products from connected HHs in rural areas, who are able to diversify their income through off-farm revenues and non-agricultural entrepreneurship, while accessing financial services through mobile money account ownership.

However, this study does not paint a complete picture of how mobile connectivity enhances the functioning of food markets and rural livelihoods in West Africa. It focuses on access to mobile and internet networks, emphasizing the role of mobile money, but does not explore other specific uses of mobile services that may have led to observed agricultural transformations and increased food demand. Such transformations could result from a variety of factors, such as horizontal searches for market information through private networks, vertical information provision via centralized market information systems, or the adoption of agricultural technologies through digital agricultural extension programs.

Overall, this analysis underlines the need to continue efforts to extend network coverage and improve its quality, but also to encourage the digital absorption capacity of households, especially those located in rural areas. While our results point to a global positive effect on food market functioning and rural livelihoods, they also highlight the risk of impoverishment of poorly digitalized households facing rising food prices in connected areas. Thus, the usage gap, rather than the connectivity gap, can be a factor in growing spatial and economic inequalities observed in the region. Beyond the extension of mobile internet network coverage, policies to support households with low digital absorptive capacity in areas undergoing digital transition therefore appear necessary.

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FROM PHONE ACCESS TO FOOD MARKETS: IS MOBILE CONNECTIVITY TRANSFORMING WEST-AFRICAN LIVELIHOODS?

APPENDIX

Table of content

A. A. Variable definitions and descriptive statistics

A.1. Dependent variable definitions.

Dependent variable:	Mathematical expression	Observation level
Natural logarithm of the price (XOF) of a commodity-unit pair j sold in the EA z	Ln $P_{z,j}$	EA-product
Price per gram (XOF) of a commodity j sold in the EA z	$P_{z,j}$	EA-product
Standard error of commodity prices observed in EAs, at the district level	$CV_{d,j}=\frac{\sigma_p}{\bar{P}d,j}$ With $\bar{P}$ the average price of the product j, and σ_p the standard deviation of the price, in district *d*	District-product
Natural logarithm of the quantity of a given commodity consumed by a household member m in the 7 days preceding the survey.	Ln $QCO_{j,m}$	HH-product
Natural logarithm of the quantity of a given commodity auto consumed by a household member m in the 7 days preceding the survey.	Ln $QACO_{j,m}$	HH-product
Natural logarithm of the quantity of a given commodity purchased by a member m in the 7 days preceding the survey.	Ln $QPU_{j,m}$	HH-product
Annual food spending per HH member (XOF, ln)	Ln $CONSF_m$	HH
Annual non-food spending per HH member (XOF, ln)	Ln $CONSNF_m$	HH
Total annual spending per HH member (XOF, ln)	Ln TOT_m	HH

Source: authors. Data drawn from LSMS (World Bank/WAEMU). The index j corresponds to commodity, m to households, z to enumeration areas, d to districts.

A.2. Dependent variables, descriptive statistics.

Variables	No. obs.	Mean	SD	Min	Max
P_{zj} - Price level, XOF/gram*	**Observation unit: EA**				
Sugar	4,650	0.66	0.46	0.05	16.67
Fresh onions	4,476	0.64	0.40	0.02	9.95
Salt	4,302	0.26	0.27	0.00	10.00
Chili pepper	4,286	2.39	2.92	0.02	59.75
Fresh tomatoes	3,720	0.66	0.61	0.02	14.83
Imported rice/broken grains	3,444	0.42	0.40	0.15	22.81
Fresh okra	3,392	0.88	0.70	0.00	21.79
Beef (with bone)	3,042	2.37	1.45	0.20	47.46
Peanut butter	3,024	1.05	0.65	0.10	13.19
Live chicken	2,795	2.21	0.77	0.55	8.46
Potatoes	2,635	0.61	0.28	0.12	6.92
Peanut oil	2,280	1.07	1.48	0.03	36.87
CV_{dj} - Price dispersion (x100=%, all prod.)	**Observation unit: EA-product**				
Coef. of var., unconverted price	19,363	0.21	0.24	0	3.598
Coef. of var., converted price	25,837	0.40	0.34	0	5.320
Ln QPU_{jh} - Purchased quant., ln grams*	**Observation unit: HH**				
Salt	33 136	4.19	1.09	0.93	11.55
Sugar	36 227	4.37	1.25	0.85	10.71
Bouillon cube	29 875	2.13	1.30	0.17	8.28
Chili	29 494	2.50	1.16	0.23	7.73
Imported rice	13 316	6.68	1.45	3.41	12.17
Fresh tomatoes	22 381	4.17	1.08	1.16	10.63
Refined palm oil	12 687	4.05	1.38	0.63	9.43
Fermented locust bean	16 825	2.45	1.06	0.11	7.79
Fresh onions	35 310	4.17	1.18	0.78	10.13
Tea	8 267	2.40	1.31	0.03	7.97
Garlic	18 238	2.11	0.97	0.24	7.60
Fresh okra	13 977	3.56	1.17	0.54	9.13
Coffee	10 441	4.26	1.27	1.07	8.52
Peanut oil	10 288	4.43	1.39	1.08	9.21
Red palm oil	10 441	4.26	1.27	1.07	8.52
Ln QCO_{jh} - Consumed quant., ln grams*	**Observation unit: HH**				
Salt	39 961	3.91	0.96	0.14	9.43
Sugar	39 190	4.81	1.06	0.29	10.06
Bouillon cube	32 423	2.96	0.96	0.13	8.63
Chili	37 098	3.18	1.07	0.13	7.67
Imported rice	16 033	6.60	0.77	3.36	10.13
Fresh tomatoes	25 885	4.85	0.94	1.25	10.08
Refined palm oil	13 689	4.42	0.96	0.80	8.96
Fermented locust bean	21 592	2.91	0.96	0.18	7.57
Fresh onions	38 549	4.75	0.93	0.00	10.31
Tea	13 474	3.18	1.28	0.05	8.16
Garlic	19 645	2.55	0.91	0.21	7.24

Fresh okra	19 678	4.11	1.00	0.76	10.04
Coffee	9 415	2.15	1.34	0.03	8.29
Red palm oil	13 313	4.22	1.01	0.63	7.66
Household spending, ln XOF		**Observation unit: HH**			
Total expenses / HH member	59,318	12.79	0.72	10.0	16.52
Food expenses / HH member	59,318	12.13	0.71	8.55	15.99
Non-food expenses / HH member	59,318	11.96	0.85	8.89	16.44

Source: authors. Data from LSMS (World Bank/WAEMU). Notes: * not all commodities and associated statistics are shown in the table. Only the first price record, and most traded commodities' price, are reported.

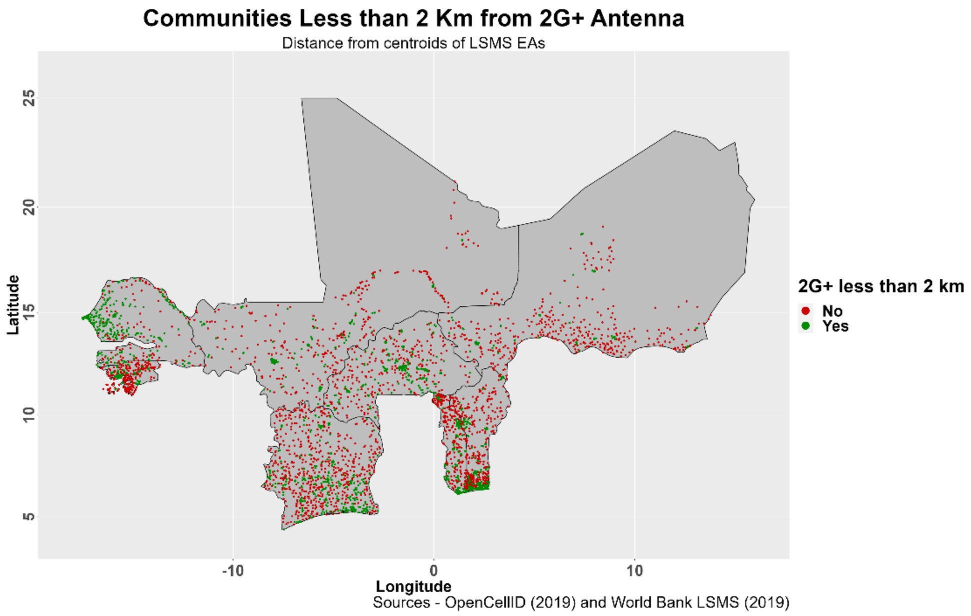
A.3. Digitalization variables

A.3.1. Descriptive statistics for digitalization variables.

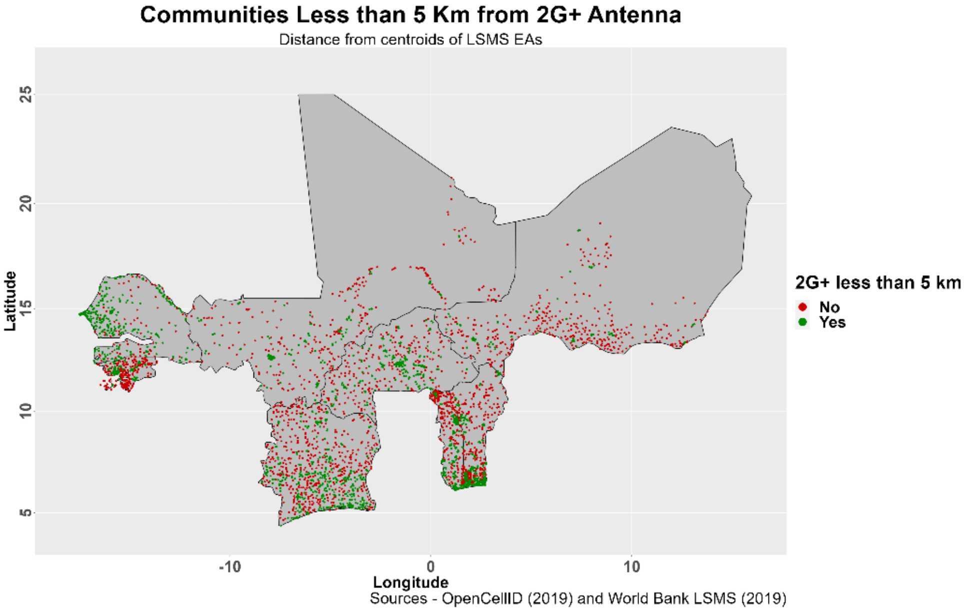
Variable	Unit	# obs	Mean	SD	Min	Max
Adoption - mobile:						
No. mobiles in HHs	HH	59,318	1.99	1.79	0	20
*Dummy at least 1 mobile in HH (0/1)**	*HH*	*59,318*	*0.89*	*0.31*	*0*	*1*
Adoption - internet:						
Dummy internet usage by the HH	HH	59,318	0.30	0.46	0	1
Connectivity:						
Mobile internet network distance, km	EA	4,646	14.22	28.09	0	318.07
Dummy internet network distance < 5km	EA	4,644	0.56	0.49	0	1
Dummy internet network distance < 2km	EA	4,645	0.51	0.50	0	1
Mobile network coverage (%)	District	488	0.185	0.288	0	1

Source: authors. Data from EHCVM (World Bank/UEMOA). Notes: the distance variable is transformed into logarithms in the econometric analysis. *Not used in the analysis.

A.3.2. Mapping of 2km proximity to cell-tower dummy.



A.3.3. Mapping of 2km and 5km proximity to cell-tower dummy.



A.4. Most-traded product-unit pairs: number of EAs trading the product-unit pair.

Product-unit pairs ordered by occurrence in EAs:	BFA	BEN	CIV	GNB	MLI	NER	SEN	TGO	# trading EAs
Salt - sachet - small	542	607	821	246	457	472	417	339	**3901**
Sugar (powder or lumps) - kg	545	172	936	340	533	358	556	56	**3496**
Tomato paste - tin - small	548	639	528	0	409	454	0	493	**3071**
Fresh tomato - heap - small	446	540	815	0	347	78	254	434	**2914**
Fresh okra - heap - small	334	569	755	0	326	40	342	423	**2789**
Fresh onion - heap - small	440	512	633	0	262	296	175	450	**2768**
Imported long grain / broken rice - kg	427	201	962	0	245	326	504	53	**2718**
Red palm oil - liter	373	530	402	293	249	0	491	292	**2630**
Whole chicken - unit (pod, etc.) - medium	1	553	573	0	436	309	373	371	**2616**
Peanut butter - bag - small	396	326	407	51	272	237	377	418	**2484**
Potato - kg	249	266	533	233	427	221	534	5	**2468**
Pepper - heap - small	375	396	788	0	261	73	185	335	**2413**
Peanut oil - liter	266	597	18	255	389	181	295	380	**2381**
Afintin/soumbala (Fermented locust bean) - ball - small	474	542	462	0	377	0	74	214	**2143**
Beef – with bone - kg	1	360	895	0	430	198	0	249	**2133**
Dry okra - bag - small	414	219	375	0	0	376	371	363	**2118**
Ginger - heap - small	301	444	547	0	265	0	0	457	**2014**
Imported broken rice - kg	6	124	817	347	319	0	289	22	**1924**
Modern bread - unit (pod, etc.) - medium	333	375	674	0	137	327	0	63	**1909**
Pasta - sachet - small	278	524	399	139	205	48	131	185	**1909**
Refined palm oil - liter	1	0	827	353	0	424	278	0	**1883**
Yam - heap - medium	99	516	701	0	126	88	0	319	**1849**
Garlic - sachet - small	398	594	24	0	224	0	191	417	**1848**
Other local rice - kg	546	84	550	22	337	10	283	0	**1832**
Fritters, cakes - unit (pod, etc.) - small	521	429	387	0	0	0	0	447	**1784**
Eggplant, pumpkin/zucchini - heap - small	282	115	763	0	118	120	61	309	**1768**
Shea butter - ball - small	391	457	181	0	373	0	45	213	**1660**

Milk powder - kg	409	0	271	87	239	155	451	0	**1612**
Local long grain / broken rice - kg	120	254	425	82	376	10	337	7	**1611**
Eggs - unit (pod, etc.)	480	0	550	302	0	0	0	243	**1575**
Sweetened condensed milk - tin - large	0	593	949	0	0	0	0	0	**1542**
Various types of fish 2 - unit (pod, etc.) - small	60	458	323	0	41	59	231	335	**1507**
Attiéke - bag - small	302	234	732	0	159	0	8	68	**1503**
Fresh / frozen mackerel / sea bream - kg	416	439	269	41	80	99	85	69	**1498**
Dried fish - heap - small	184	380	257	0	333	91	45	179	**1469**
Sweet potato - heap - small	1	431	429	0	0	320	58	211	**1450**
Grain maize - 100 kg bag	366	331	79	0	257	338	30	34	**1435**
Orange - heap - small	143	363	402	0	129	114	0	252	**1403**
Millet - kg	7	17	480	32	365	0	500	0	**1401**
Cucumber - unit (pod, etc.) - small	272	222	664	0	236	0	0	0	**1394**
Traditional bread - unit (pod, etc.) - small	0	416	208	0	133	196	0	377	**1330**
Local or imported wheat flour - kg	1	353	590	0	0	339	0	46	**1329**
Fresh fish (sea bream and others) - kg	413	162	457	15	82	77	78	38	**1322**
Fresh fish (carp and others) - kg	332	93	318	35	115	58	115	243	**1309**
Curdled milk, yogurt - sachet - small	1	287	285	153	0	96	359	124	**1305**
Tea - packet - small	0	0	221	64	0	445	547	0	**1277**
Lemons - heap - small	1	501	480	0	0	0	0	294	**1276**
Bouillon cube (Maggi, Jumbo) - unit (pod, etc.) - large	0	0	879	0	0	339	0	0	**1218**
Mutton - kg	1	190	331	0	0	166	393	110	**1191**
Cassava - heap - small	1	368	427	0	0	136	71	172	**1175**
Traditional beers and wines (dolo, palm wine, etc.) - liter	381	183	291	207	0	0	0	101	**1163**
Offal and tripe (liver, kidney, etc.) - kg	1	206	542	142	0	34	0	197	**1122**
Cakes - unit (pod, etc.) - small	442	279	205	0	0	0	0	177	**1103**
Dates - bag - small	1	399	213	11	0	337	0	132	**1093**
Sorrel leaves - heap - small	262	107	61	0	259	62	212	128	**1091**
Roasted peanuts - bag - small	1	534	185	0	0	0	0	362	**1082**
Cowpeas/dried beans - kg	4	19	532	0	0	43	463	0	**1061**

Sweet banana - heap - medium	266	109	378	0	195	0	0	91	**1039**
Soft drinks (Coke, etc.) - bottle - medium	0	0	623	13	0	397	0	0	**1033**
Plaintain - heap - medium	156	0	649	0	165	0	4	54	**1028**
Fresh milk - liter	0	80	289	101	319	41	143	40	**1013**
Sorghum - 100 kg bag	330	138	13	0	243	269	0	16	**1009**
Fruit juices (orange, bissap, ginger, etc.) - bag - small	0	480	406	114	0	0	0	0	**1000**
Various leaves (adémé) - heap - small	0	375	108	141	0	28	0	345	**997**
Shelled or crushed peanuts - bag - small	1	194	230	0	0	0	338	231	**994**
Green beans - heap - small	27	230	419	0	103	0	0	203	**982**
Baobab leaves - heap - small	274	133	120	0	177	45	0	205	**954**
Fresh bell pepper - unit (pod, etc.) - small	318	156	221	0	255	0	0	0	**950**
Mango - heap - small	198	221	153	0	182	0	0	191	**945**
Chicken meat - kg	1	259	198	188	0	0	89	204	**939**
Goat meat - kg	1	128	185	62	0	116	313	115	**920**
Bean leaves / gboma - bunch - small	1	376	282	0	0	0	0	239	**898**
Coffee - bag - small	0	0	434	0	0	0	463	0	**897**
Honey - liter	0	300	269	114	0	63	0	146	**892**
Pineapple - unit (pod, etc.) - medium	129	345	381	0	0	0	0	0	**855**
Carrot - bunch - small	1	338	111	0	0	0	114	262	**826**
Unsweetened condensed milk - tin - small	0	0	824	0	0	0	0	0	**824**
Salad (lettuce) - heap - small	123	102	50	53	224	68	0	204	**824**
Smoked fish (various types) - unit (pod, etc.) - medium	0	435	316	0	0	0	68	0	**819**
Various types of fish 1 - kg	0	526	119	47	0	0	48	70	**810**
Sesame - bag - small	1	472	25	0	0	0	0	309	**807**
Cookies - unit (pod, etc.) - small	0	324	221	0	0	0	0	255	**800**
Kola nuts - unit (pod, etc.) - small	1	357	435	0	0	0	0	0	**793**
Cabbage - unit (pod, etc.) - small	0	277	123	0	0	0	248	113	**761**
Peas - can - small	1	309	307	0	0	0	0	141	**758**
Avocados - unit (pod, etc.) - medium	1	277	473	0	0	0	0	0	**751**
Gari, tapioca - bag - small	0	312	184	0	0	0	0	220	**716**

Butter - jar - small	0	0	228	0	158	0	211	0	**597**
Mineral/filtered water - bottle - large	0	0	314	281	0	0	0	0	**595**
Local cheese - unit (pod, etc.) - small	0	355	0	0	0	0	0	230	**585**
Coconut - unit (pod, etc.) - medium	1	367	196	0	0	0	0	0	**564**
Corn flour - bag - small	122	74	228	0	10	81	0	30	**545**
Watermelon, Melon - unit (pod, etc.) - small	1	251	40	0	0	199	54	0	**545**
Cottonseed oil - liter	320	0	13	0	188	0	0	0	**521**
Industrial beer - bottle - Mean	0	0	385	129	0	0	0	0	**514**
Pork - piece - small	0	167	219	3	29	0	0	94	**512**
Canned fish - tin - small	0	338	165	0	0	0	0	0	**503**
Vinegar/mustard - bottle - small	0	250	192	54	0	0	0	0	**496**
Calabash - package - one size	493	0	0	0	0	0	0	0	**493**
Crabs, shrimps and other seafood - heap - small	0	268	104	0	0	0	0	107	**479**
Fonio - kg	19	2	209	0	234	0	0	0	**464**
Mayonnaise - bottle - small	0	0	139	313	0	0	0	0	**452**
Dried tomato - bag - small	138	139	140	0	0	0	0	29	**446**
Taro, macabo - heap - small	1	143	189	0	0	0	0	87	**420**
Caramel, sweets, etc. - unit (pod, etc.) - small	0	0	374	0	0	0	0	0	**374**
Cassava flour - bag - medium	1	86	278	0	0	0	0	0	**365**
Peanut oil (segal) / lemon vinegar - liter	0	0	0	217	0	0	130	0	**347**
Corn on the cob - heap - small	0	167	128	0	0	0	0	32	**327**
Fresh peanuts in shell - kg	0	0	25	189	0	0	111	0	**325**
Papaya - bag - small	278	0	0	0	0	0	0	0	**278**
Other condiments (pepper, etc.) - sachet - small	0	0	258	0	0	0	0	0	**258**
Sugar cane - unit (pod, etc.) - small	1	241	12	0	0	0	0	0	**254**
Croissants - unit (pod, etc.) - medium	0	129	109	0	0	0	0	13	**251**
African eggplant - unit (pod, etc.)	0	0	0	249	0	0	0	0	**249**
Chocolate spread - bag - small	0	0	233	0	0	0	0	0	**233**
Cassava leaves, taro leaves and other leaves - heap - small	0	104	31	0	0	0	0	85	**220**
Other herbal teas and infusions n.e.c. (quinquelibat, citronella, etc.) - liter	0	57	2	0	0	0	0	130	**189**

Oil palm fruit - small	0	0	0	183	0	0	0	0	**183**
Dried peanuts in shell - heap - small	1	54	110	0	0	0	0	8	**173**
Black tamarind - sachet - small	0	0	0	144	0	0	0	0	**144**
Chocolate powder - sachet - small	0	0	133	0	0	0	0	0	**133**
Baby milk and flour - tin - Mean	0	0	130	0	0	0	0	0	**130**
Cashew nuts - kg	0	70	32	0	0	0	0	0	**102**
Juice powder - sachet - small	0	0	92	0	0	0	0	0	**92**
Other pulses n.e.s. - kg	0	0	24	65	0	0	0	0	**89**
Millet flour - sachet - medium	0	0	85	0	0	0	0	0	**85**
Flavorings (Maggi, Jumbo) - bottle - small	0	0	84	0	0	0	0	0	**84**
Game - kg	0	0	2	69	0	0	0	0	**71**
Rubber vine fruit - unit (pod, etc.)	0	0	0	58	0	0	0	0	**58**
Other cereals - kg	1	0	56	0	0	0	0	0	**57**
Other fruit (apples, grapes, etc.) - unit (pod, etc.)	0	0	56	0	0	0	0	0	**56**
Shea nuts - tub - other size 1	0	55	0	0	0	0	0	0	**55**
Wheat - kg	1	0	53	0	0	0	0	0	**54**
Other fresh vegetables n.e.c. - heap - small	0	0	45	0	0	0	0	0	**45**
Meat of other domestic fowl - unit (pod, etc.) - large	0	0	43	0	0	0	0	0	**43**
Other food products - bag - small	0	0	39	0	0	0	0	0	**39**
Dried peas - tin - small	1	30	0	0	0	0	0	1	**32**
Cured and preserved meats - tin - small	0	0	31	0	0	0	0	0	**31**
Other oils n.e.c. (corn, palm kernel, soybean, etc.) - bottle - medium	0	0	23	0	0	0	0	0	**23**
Other citrus fruits - heap - medium	0	0	20	0	0	0	0	0	**20**
Other dairy products - jar - small	0	0	13	0	0	0	0	0	**13**
Other meats n.e.c. - piece - large	0	0	11	0	0	0	0	0	**11**
Other cereal flours - sachet - medium	0	0	9	0	0	0	0	0	**9**
Other cereal flours - sachet - small	0	0	9	0	0	0	0	0	**9**
Other tubers - bag - large	0	0	8	0	0	0	0	0	**8**
Other tubers - bag - small	0	0	8	0	0	0	0	0	**8**

A.5. Household control variables, descriptive statistics.

Variable	# obs	Average	Std. dev.	Min	Max
Panel A. HHH characteristics:					
No education (0/1)	59,282	0.5998785	0.4899269	0	1
Primary education (0/1)	59,282	0.1809318	0.3849649	0	1
Secondary gen 1 (0/1)	59,282	0.095965	0.2945458	0	1
Secondary gen 2 (0/1)	59,282	0.0530178	0.2240708	0	1
HHH literacy (0/1)	59,282	0.4863365	0.4998175	0	1
HHH gender (0/1)	59,282	1.189956	0.3922698	1	2
HHH age	59,282	45.63658	14.66437	12	105
Married monogamous (0/1)	59,282	0.5876489	0.4922619	0	1
Married polygamist (0/1)	59,282	0.1872913	0.3901484	0	1
Panel B. HH demographic characteristics:					
Household size	59,282	6.171148	4.167168	1	59
No. adults-equiv. FAO	59,282	4.567125	3.06689	0.66	43.265
Panel C. HH Housing characteristics:					
Tenant (0/1)	59,282	0.1627138	0.3691075	0	1
Wall in final materials (0/1)	59,282	0.6710469	0.4698369	0	1
Roof in final materials (0/1)	59,282	0.7518302	0.4319545	0	1
Floor in final materials (0/1)	59,282	0.6477683	0.4776697	0	1
Panel D. HH living standards:					
TV (0/1)	59,282	0.3197429	0.4663808	0	1
Iron (0/1)	59,282	0.0406194	0.1974085	0	1
Fridge (0/1)	59,282	0.1014305	0.3019004	0	1
Kitchen (0/1)	59,282	0.04234	0.2013654	0	1
Computer (0/1)	59,282	0.0440775	0.205269	0	1
Decoder (0/1)	59,282	0.1343578	0.3410392	0	1
Owns car (0/1)	59,282	0.0286934	0.1669447	0	1
Banked (0/1)	59,282	0.169042	0.2653388	0	1
Total expenses	56,829	12.77	0.71	10.04	16.52
Panel E. Infrastructure access:					
Uses elec. grid (0/1)	59,282	0.3766236	0.4845433	0	1
Uses solar elec/genset. (0/1)	59,282	0.1989643	0.3992245	0	1
Improved waste disposal (0/1)	59,282	0.2687662	0.4433218	0	1
Improved toilets (0/1)	59,282	0.2592861	0.4382466	0	1
Improved human waste disposal (0/1)	59,282	0.2611923	0.4392882	0	1
Improved sewage disposal (0/1)	59,282	0.095071	0.2933155	0	1
Panel F. HH exposure to shocks:					
Idiosyncratic demographic shocks	59,318	0.3519168	0.4775722	0	1
Idiosyncratic economic shocks	59,318	0.1477123	0.3548176	0	1
Covariant natural shocks	59,318	0.308473	0.4618669	0	1
Covariant economic shocks	59,318	0.2327624	0.4225956	0	1
Covariant violence shocks	59,318	0.0535251	0.22508	0	1
Other shocks	59,318	0.0197411	0.1391103	0	1
Panel G. HH crop characteristics:					

Rainfed/irrigated surface area ratio	59,282	6.46242	301.3123	0	50115
Total area of plots	59,282	9.40532	401.1745	0	50115

Source: authors. Data taken from LSMS (World Bank/WAEMU). Note: the tenant dummy equals 1 if the household is a tenant (17%), 0 if the household is an owner with title (17%) or without title (58%), or other (16%).

A.6. Enumeration Area (EA) or "community" control variables, descriptive statistics.

Variable	# obs	Mean	SD	Min	Max
Economic development:					
Night light density	4,618	13.737	17.812	2.85	63.00
Motorized collective transport (0/1)	4,618	0.796	0.403	0.00	1.00
Electric distribution network	4,962	0.539	0.499	0	1
Water distribution network	4,962	0.482	0.500	0	1
Among the 2 main economic activities in the EA:					
Cereals/tubers (0/1)	4,620	0.547	0.498	0.00	1.00
Annuity products (0/1)	4,620	0.131	0.338	0.00	1.00
Market garden products (0/1)	4,620	0.019	0.135	0.00	1.00
Livestock (0/1)	4,620	0.041	0.199	0.00	1.00
Fishery (0/1)	4,620	0.022	0.146	0.00	1.00
Mining, gold panning (0/1)	4,620	0.002	0.044	0.00	1.00
Trade (0/1)	4,620	0.086	0.281	0.00	1.00
Crafts, Processing (0/1)	4,620	0.113	0.317	0.00	1.00
Services (0/1)	4,620	0.036	0.186	0.00	1.00
Demography:					
Population density	4,618	1181.002	3536.618	0.13	34944.11
Number of households surveyed	4,618	11.918	0.440	5.00	12.00
Number of inhabitants in the EA (ln)	4,618	7.861	1.279	0.00	13.12
Geography:					
Urban EA (0/1)	4,618	0.401	0.490	0.00	1.00
Distance to the closest city (ln, km)	4,618	2.047	1.506	0.00	5.60
Hills/mountains (0/1)	4,956	0.160	0.366	0.00	1.00
Plaine (0/1)	4,956	0.475	0.499	0.00	1.00
Gentle slope (0/1)	4,956	0.231	0.421	0.00	1.00
Steep slope (0/1)	4,956	0.035	0.183	0.00	1.00
Valley (0/1)	4,956	0.076	0.266	0.00	1.00
Lake City (0/1)	4,956	0.009	0.093	0.00	1.00
Cuvette (0/1)	4,956	0.003	0.057	0.00	1.00
Altitude (m)	4,618	226.115	156.444	-168.00	1539.00

Source: authors. Data from LSMS (World Bank/WAEMU).

A.7. Raster Dataset Specifications:

A.7.1. Population density

Database: SEDAC Gridded Population of the World:

Resolution:

- netCDF-4 (all years combined) – 2.5 arc minutes (~5km at the Equator)
- Geo_tiff (2010, 2015) – 30 arc second (~1km at the Equator)
- CRS: WGS84 (Geographic Latitude/Longitude)

A.7.2. Nighttime lights density

Database: Version 4 DMSP-OLS Nighttime Lights

Resolution:

- 30 arc second (~1km at the Equator)
- CRS: EPSG:4326 (Geographic Latitude/Longitude)

A.7.3. Lightning strikes density

Database: LIS 0.1 Degree Very High Resolution Gridded Lightning Climatology Data Collection:

Resolution:

- degrees (6 arc minutes / ~11.13 km at the Equator)
- Units: flashes/km2/day

A.8. Definition of shock variables in LSMS

Idiosyncratic Demographic Shocks:
- Death of a household member
- Divorce, separation

Natural Covariant Shocks:
- Drought/Irregular rains
- Floods
- Fires
- Landslides

Economic Covariant Shocks:
- High rates of crop diseases
- High rates of animal diseases
- Significant decrease in agricultural product prices
- High prices of agricultural inputs
- High prices of food products

Idiosyncratic Economic Shocks:
- End of regular transfers from other households

- Significant loss of non-agricultural income of the household (other than due to an accident or illness)
- Bankruptcy of a non-agricultural business of the household
- Significant loss of wage income (other than due to an accident or illness)
- Job loss of a wage-earning member
- Theft of money, goods, harvest, or livestock

Violence Covariant Shocks:
- Farmer/Herder conflict
- Armed conflict/Violence/Insecurity
- Locust attacks or other crop pests

Other Shocks:
- Other (to be specified)

B. B. Baseline estimations: additional information.

B.1. First-stage estimates, Eq (3).

	(1) Dist. 2G+. (ln, km)	(2) Dist < 5km	(3) Dist < 2km
VI – Lightning risk	811.5***	-271.7***	-260.3***
	(113.6)	(37.16)	(48.15)
Altitude (m)	0.00136***	-0.000372**	-0.000361**
	(0.000444)	(0.000154)	(0.000150)
Hills/mountains (% EA)	-0.0144	0.00301	0.0184
	(0.0914)	(0.0298)	(0.0251)
Plaine (% EA)	0.0178	-0.00539	0.00819
	(0.0824)	(0.0267)	(0.0210)
Gentle slope (% EA)	0.0393	-0.0140	0.00739
	(0.0877)	(0.0294)	(0.0239)
Steep slope (% EA)	0.0506	0.0122	0.0147
	(0.101)	(0.0358)	(0.0319)
Valley (% EA)	0.0544	-0.0236	-0.0130
	(0.0971)	(0.0331)	(0.0275)
Lake City (% EA)	0.0765	-0.00828	0.0111
	(0.139)	(0.0465)	(0.0467)
Cuvette (% EA)	0.189	-0.0528	-0.0515
	(0.148)	(0.0528)	(0.0481)
Night lights density	-0.00765***	0.00183*	0.00291***
	(0.00284)	(0.000945)	(0.00101)
Population density	0.00000449	-0.00000116	-0.00000147
	(0.00000717)	(0.00000228)	(0.00000236)
Number of surveyed HHs	-0.173	0.0541	0.0158
	(0.377)	(0.154)	(0.152)
Ln # of inhab. in the EA	0.00584	-0.00170	0.000956
	(0.0145)	(0.00535)	(0.00521)
Electric distribution network	0.119	-0.00649	-0.0138
	(0.393)	(0.134)	(0.134)
Running water network	0.0763	0.0225	-0.00627
	(0.381)	(0.131)	(0.130)
Cereals/tubers	0.138	0.0142	-0.0425
	(0.414)	(0.141)	(0.142)
Livestock	0.237	-0.0155	0.00391
	(0.404)	(0.137)	(0.137)
Fishing	0.0840	-0.0152	0.00688
	(0.409)	(0.140)	(0.140)
Mining, gold panning	-0.682	0.255*	0.329**
	(0.469)	(0.152)	(0.154)
Trade	0.100	-0.00998	-0.00536
	(0.403)	(0.137)	(0.136)
Craftsmanship, Processing	0.133	-0.0185	-0.0167
	(0.398)	(0.135)	(0.135)
Services	0.160	-0.0284	-0.0226
	(0.401)	(0.136)	(0.136)
Other activities	-0.0332	-0.0169	0.0346
	(0.440)	(0.152)	(0.156)
Distance (ln, km) to city	0.226***	-0.0704***	-0.0653***
	(0.0222)	(0.00742)	(0.00724)
Motorized collective transport	-0.117***	0.0336*	0.0292*
	(0.0436)	(0.0174)	(0.0154)
Urban EA	-0.242***	0.0939***	0.124***
	(0.0615)	(0.0230)	(0.0238)
Household size	0.137**	-0.0507**	-0.0591**
	(0.0679)	(0.0240)	(0.0247)

# adults-equiv. FAO	-0.197**	0.0732**	0.0815**
	(0.0908)	(0.0320)	(0.0329)
HHH gender (%HH)	-0.102	0.0602	0.00389
	(0.125)	(0.0469)	(0.0459)
Age of HHH	0.000527	-0.00126	-0.00104
	(0.00296)	(0.00115)	(0.00117)
Literacy of HHH (%HH)	-0.129	0.0274	0.0469
	(0.104)	(0.0396)	(0.0393)
Married monogamous (%HH)	0.000736	0.0144	0.00333
	(0.123)	(0.0475)	(0.0472)
Married polygamous (%HH)	0.322**	-0.0608	-0.0746
	(0.150)	(0.0587)	(0.0586)
Banked (%HH)	-0.0482	0.0498	0.0324
	(0.181)	(0.0626)	(0.0661)
No education (%HH)	-0.129	0.0303	0.0248
	(0.177)	(0.0605)	(0.0597)
Primary education (%HH)	0.0639	-0.0191	-0.0541
	(0.177)	(0.0603)	(0.0615)
Secondary ed. 1 (%HH)	-0.0215	0.00942	-0.0301
	(0.181)	(0.0680)	(0.0684)
Secondary ed. 2 (%HH)	0.0476	0.0368	0.0179
	(0.206)	(0.0710)	(0.0722)
Uses electric network (%HH)	-0.198*	0.0686*	0.0419
	(0.101)	(0.0412)	(0.0399)
Uses solar elec./group elec. (%HH)	0.230**	-0.0538	-0.0812**
	(0.104)	(0.0413)	(0.0379)
Improved waste disposal (%HH)	0.170**	-0.0576**	-0.0610**
	(0.0775)	(0.0289)	(0.0291)
Improved toiled (%HH)	0.0688	-0.0397	-0.0285
	(0.0889)	(0.0315)	(0.0345)
Improved human waste disposal (%HH)	0.0104	-0.00144	0.000383
	(0.0779)	(0.0284)	(0.0295)
Improved sewage disposal (%HH)	-0.0412	0.0256	0.0175
	(0.102)	(0.0349)	(0.0379)
Demographic idiosync. Shocks (%HH)	-0.0315	-0.00829	0.00944
	(0.0793)	(0.0301)	(0.0295)
Natural covariant shocks (%HH)	0.455***	-0.133***	-0.138***
	(0.0855)	(0.0327)	(0.0306)
Economic covariant shocks (%HH)	-0.0305	0.00196	0.00597
	(0.0815)	(0.0330)	(0.0319)
Economic idiosync. Shocks (%HH)	-0.286***	0.0864**	0.106***
	(0.0960)	(0.0370)	(0.0383)
Violence covariant shocks (%HH)	-0.101	0.0901	0.0284
	(0.167)	(0.0665)	(0.0656)
Other covariant shocks (%HH)	0.244	-0.244**	-0.0544
	(0.299)	(0.108)	(0.105)
Av. rainfed/irrigated surface area ratio	-0.000184	0.000119	0.0000360
	(0.000362)	(0.000167)	(0.000151)
Total plot area (ha)	0.000725	-0.000135	-0.000528***
	(0.000531)	(0.000242)	(0.000196)
Rents land	0.0265	-0.0303	0.0300
	(0.107)	(0.0384)	(0.0403)
Walls - finished materials (%HH)	-0.150	0.0260	0.0471
	(0.0911)	(0.0395)	(0.0330)
Roof - finished materials (%HH)	-0.0841	0.0449	0.0439
	(0.132)	(0.0508)	(0.0470)
Floor - finished material (%HH)	-0.454***	0.174***	0.161***
	(0.119)	(0.0466)	(0.0456)
TV (%HH)	0.0847	-0.0312	-0.00256
	(0.125)	(0.0482)	(0.0479)
Has iron (%HH)	0.0276	-0.00819	0.0358
	(0.155)	(0.0538)	(0.0595)

Has fridge (%HH)	0.397***	-0.0991**	-0.133***
	(0.130)	(0.0488)	(0.0512)
Has kitchen (%HH)	-0.261	0.0734	0.0657
	(0.234)	(0.0769)	(0.0720)
Owns computer (%HH)	0.532***	-0.156***	-0.211***
	(0.164)	(0.0560)	(0.0615)
Owns decoder (%HH)	-0.282**	0.0372	0.0737*
	(0.129)	(0.0452)	(0.0447)
Owns car (%HH)	-0.206	0.0659	0.0693
	(0.198)	(0.0647)	(0.0694)
Constant	1.710	0.442	0.488
	(1.074)	(0.430)	(0.420)
District FEs	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes
Observations	4,647	4,645	4,646
R^2	0.775	0.651	0.676

Standard errors in brackets, robust to heteroskedasticity and clustered by district. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.2. Estimations of Eq. (4)

B.2.1. OLS Estimation of Eq. (4).

Dep. var: Ln $P_{z,i}$ (record 1)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Distance 2G/3G/4G (ln, km)	-0.015***			-0.006***			-0.011***		
	(0.00132)			(0.002)			(0.002)		
2/3/4G <2km (0/1)		0.037***			0.012***			0.024***	
		(0.004)			(0.004)			(0.005)	
2/3/4G <5km (0/1)			0.035***			0.013***			0.026***
			(0.003)			(0.004)			(0.005)
Hills/mountains (0/1)				-0.016	-0.015	-0.015	-0.022	-0.021	-0.022
				(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)
Plaine (0/1)				-0.019	-0.019	-0.019	-0.029**	-0.028**	-0.028*
				(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Gentle slope (0/1)				-0.024*	-0.024*	-0.024*	-0.036**	-0.036**	-0.036**
				(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)
Steep slope (0/1)				-0.009	-0.009	-0.009	-0.024	-0.024	-0.025
				(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)
Valley (0/1)				-0.016	-0.016	-0.016	-0.030**	-0.030**	-0.030*
				(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Lake City (0/1)				0.021	0.020	0.021	-0.008	-0.009	-0.008
				(0.022)	(0.022)	(0.022)	(0.024)	(0.024)	(0.024)
Cuvette (0/1)				0.000	0.001	0.001	-0.024	-0.023	-0.024
				(0.028)	(0.028)	(0.028)	(0.034)	(0.034)	(0.034)
Nighttime light density				0.000***	0.000***	0.000***	0.001***	0.001***	0.001***
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density				-0.000*	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of surveyed HHs				-0.015	-0.014	-0.015	-0.149***	-0.148***	-0.149***
				(0.028)	(0.028)	(0.028)	(0.034)	(0.034)	(0.034)
# of inhab. in EAs				-0.004***	-0.004***	-0.004***	-0.005***	-0.005***	-0.005***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Elec. network (0/1)				-0.003	-0.003	-0.003	-0.004	-0.003	-0.003
				(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Water network (0/1)				0.000	0.000	0.000	0.006	0.006	0.006
				(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Cereals/tubers (0/1)	-0.067**	-0.068**	-0.068**	-0.130***	-0.130***	-0.131***
	(0.029)	(0.030)	(0.030)	(0.019)	(0.019)	(0.019)
Cash crops (0/1)	-0.072**	-0.073**	-0.073**	-0.133***	-0.133***	-0.134***
	(0.030)	(0.030)	(0.030)	(0.019)	(0.019)	(0.019)
Vegetables (0/1)	-0.064**	-0.064**	-0.064**	-0.123***	-0.123***	-0.124***
	(0.031)	(0.031)	(0.031)	(0.021)	(0.021)	(0.021)
Livestock (0/1)	-0.068**	-0.069**	-0.068**	-0.125***	-0.127***	-0.126***
	(0.030)	(0.031)	(0.031)	(0.020)	(0.020)	(0.020)
Fishing (0/1)	-0.053*	-0.054*	-0.053*	-0.096***	-0.097***	-0.096***
	(0.031)	(0.032)	(0.031)	(0.021)	(0.022)	(0.022)
Mining, gold panning (0/1)	-0.062*	-0.062*	-0.062	-0.144***	-0.145***	-0.144***
	(0.037)	(0.038)	(0.038)	(0.041)	(0.041)	(0.041)
Trade (0/1)	-0.066**	-0.066**	-0.066**	-0.132***	-0.133***	-0.133***
	(0.029)	(0.030)	(0.030)	(0.019)	(0.019)	(0.019)
Crafts/Processing (0/1)	-0.070**	-0.070**	-0.070**	-0.134***	-0.135***	-0.135***
	(0.030)	(0.030)	(0.030)	(0.019)	(0.019)	(0.019)
Services (0/1)	-0.079***	-0.080***	-0.080***	-0.140***	-0.141***	-0.141***
	(0.030)	(0.031)	(0.030)	(0.020)	(0.020)	(0.020)
Other activities (0/1)	-0.079**	-0.079**	-0.079**	-0.155***	-0.155***	-0.154***
	(0.032)	(0.032)	(0.032)	(0.026)	(0.026)	(0.026)
Av. Distance (ln, km) to city	-0.003**	-0.004***	-0.003***	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Motorized collect. transp (0/1)	-0.002	-0.001	-0.002	0.003	0.004	0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Av. Altitude (m)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban (0/1)	0.017***	0.017***	0.017***	0.021***	0.020***	0.021***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Av. Household size	-0.007	-0.007	-0.007	-0.010	-0.010	-0.010
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Av. # adults in HH	0.014	0.014	0.014	0.017	0.017	0.017
	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.012)
% of male HHH	-0.018	-0.018	-0.018	-0.007	-0.007	-0.006
	(0.012)	(0.012)	(0.012)	(0.014)	(0.014)	(0.014)
Av. Age of HHH	-0.001**	-0.001**	-0.001**	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Av. literacy of HHH	-0.005	-0.005	-0.005	-0.008	-0.008	-0.008
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)

Married monogamous (% HH)	0.029	0.029	0.030	0.018	0.018	0.018
	(0.024)	(0.024)	(0.024)	(0.028)	(0.028)	(0.028)
Married polygamous (% HH)	0.013	0.012	0.013	-0.061	-0.063*	-0.061
	(0.032)	(0.032)	(0.032)	(0.038)	(0.038)	(0.038)
Banked (% HH)	0.001	0.002	0.001	0.001	0.002	0.001
	(0.022)	(0.022)	(0.022)	(0.024)	(0.024)	(0.024)
No education (% HH)	0.007	0.009	0.007	0.063*	0.065*	0.063*
	(0.033)	(0.033)	(0.033)	(0.037)	(0.037)	(0.037)
Primary education (% HH)	0.018	0.020	0.019	0.061	0.065*	0.062
	(0.034)	(0.034)	(0.034)	(0.039)	(0.039)	(0.039)
Secondary educ. (% HH)	0.022	0.024	0.023	0.086**	0.089**	0.088**
	(0.036)	(0.036)	(0.036)	(0.041)	(0.041)	(0.041)
Tot. HH spending (XOF, ln)	0.020***	0.019***	0.020***	0.030***	0.029***	0.030***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Home tenant (% HH)	0.013	0.013	0.013	0.020*	0.020*	0.021*
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Walls - finished mat. (% HH)	-0.007	-0.006	-0.006	-0.003	-0.002	-0.002
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Roof - finished mat. (% HH)	-0.008	-0.009	-0.009	-0.021*	-0.023*	-0.022*
	(0.010)	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)
Floor - finished mat. (% HH)	0.015	0.016	0.015	0.034***	0.034***	0.034***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Owns TV (% HH)	-0.034***	-0.034***	-0.034***	-0.034***	-0.034***	-0.034***
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)	(0.011)
Owns iron (% HH)	-0.014	-0.015	-0.014	-0.011	-0.013	-0.011
	(0.018)	(0.018)	(0.018)	(0.020)	(0.020)	(0.020)
Owns fridge (% HH)	0.013	0.013	0.012	0.024	0.024	0.022
	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)
Owns kitchen (% HH)	0.055***	0.056***	0.055***	0.056***	0.057***	0.056***
	(0.018)	(0.018)	(0.018)	(0.020)	(0.020)	(0.020)
Owns computer (% HH)	-0.038*	-0.039*	-0.039*	-0.019	-0.019	-0.020
	(0.022)	(0.022)	(0.022)	(0.025)	(0.025)	(0.025)
Owns decoder (% HH)	-0.017	-0.016	-0.016	-0.040***	-0.039***	-0.038***
	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)	(0.015)
Owns car (% HH)	0.022	0.023	0.022	0.021	0.022	0.021
	(0.025)	(0.025)	(0.025)	(0.029)	(0.029)	(0.029)
Demog. idio. shocks (% HH)	-0.025***	-0.025***	-0.025***	-0.024***	-0.025***	-0.023**
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Natural cov. shocks (% HH)	-0.041***	-0.041***	-0.042***	-0.026***	-0.027***	-0.028***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)

Econ. cov.shocks (% HH)				-0.008	-0.007	-0.008	0.002	0.002	0.002
				(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Econ. idio. Shocks (% HH)				-0.013	-0.014	-0.013	-0.006	-0.006	-0.005
				(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
Violence cov. shocks (% HH)				-0.057***	-0.056***	-0.057***	-0.084***	-0.083***	-0.084***
				(0.018)	(0.018)	(0.018)	(0.021)	(0.021)	(0.021)
Other cov. shocks (% HH)				0.007	0.007	0.008	0.063**	0.063*	0.066**
				(0.027)	(0.027)	(0.027)	(0.032)	(0.032)	(0.032)
Ratio rainfed/irrigated plots				-0.000	-0.000	-0.000	0.000	0.000	0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	5.273***	5.232***	5.231***	5.181***	5.171***	5.165***	4.824***	4.803***	4.778***
	(0.00201)	(0.00237)	(0.00253)	(0.133)	(0.133)	(0.134)	(0.391)	(0.390)	(0.391)
Observations	133,006	132,936	132,941	129,738	129,668	129,685	129,738	129,668	129,685
District-product-unit FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
District FE	No	No	No	No	No	No	Yes	Yes	Yes
Product-unit FE	No	No	No	No	No	No	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.967	0.967	0.967	0.967	0.967	0.967	0.922	0.922	0.922

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.2.2. 2SLS Estimation of Eq. (4).

Dep. var: Ln $P_{z,i}$	(1)	(2)	(3)	(4)	(5)	(6)
		Price record 1			Price record 2	
Distance 2G/3G/4G (ln, km)	-0.037***			-0.039***		
	(0.011)			(0.011)		
2/3/4G <2km (0/1)		0.111***			0.118***	
		(0.035)			(0.034)	
2/3/4G <5km (0/1)			0.103***			0.110***
			(0.032)			(0.032)
Hills/mountains (0/1)	-0.015	-0.015	-0.014	-0.024*	-0.024*	-0.022
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Plaine (0/1)	-0.018	-0.018	-0.016	-0.025*	-0.025*	-0.024*
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Gentle slope (0/1)	-0.025*	-0.026*	-0.024*	-0.031**	-0.032**	-0.030**
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
Steep slope (0/1)	-0.007	-0.008	-0.008	-0.013	-0.014	-0.014
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.015)
Valley (0/1)	-0.015	-0.015	-0.014	-0.019	-0.019	-0.018
	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)
Lake City (0/1)	0.009	0.006	0.009	0.016	0.014	0.017
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Cuvette (0/1)	-0.006	-0.004	-0.006	-0.005	-0.003	-0.004
	(0.032)	(0.032)	(0.033)	(0.029)	(0.029)	(0.029)
Nighttime light density	0.000**	0.000*	0.000***	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Population density	-0.000	-0.000	-0.000*	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of surveyed HHs	-0.053*	-0.048	-0.051*	-0.026	-0.021	-0.024
	(0.029)	(0.030)	(0.030)	(0.029)	(0.030)	(0.030)
# of inhab. in EAs	-0.004***	-0.004***	-0.004***	-0.003**	-0.003**	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Elec. network (0/1)	-0.009*	-0.008*	-0.008*	-0.011**	-0.010**	-0.009*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Water network (0/1)	0.003	0.002	0.004	-0.000	-0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Cereals/tubers (0/1)	-0.093***	-0.095***	-0.097***	-0.072**	-0.074**	-0.076**
	(0.020)	(0.022)	(0.022)	(0.030)	(0.032)	(0.032)
Cash crops (0/1)	-0.097***	-0.100***	-0.101***	-0.075**	-0.078**	-0.080**
	(0.020)	(0.023)	(0.022)	(0.030)	(0.033)	(0.032)
Vegetables (0/1)	-0.092***	-0.092***	-0.096***	-0.069**	-0.069**	-0.073**
	(0.022)	(0.024)	(0.023)	(0.031)	(0.034)	(0.033)
Livestock (0/1)	-0.088***	-0.094***	-0.092***	-0.070**	-0.077**	-0.075**
	(0.021)	(0.023)	(0.023)	(0.031)	(0.034)	(0.033)
Fishing (0/1)	-0.070***	-0.075***	-0.072***	-0.057*	-0.062*	-0.059*
	(0.023)	(0.025)	(0.024)	(0.031)	(0.034)	(0.033)
Mining, gold panning (0/1)	-0.091***	-0.102***	-0.093***	-0.084**	-0.096**	-0.086**
	(0.031)	(0.035)	(0.033)	(0.038)	(0.043)	(0.040)
Trade (0/1)	-0.093***	-0.095***	-0.095***	-0.070**	-0.073**	-0.073**
	(0.020)	(0.022)	(0.022)	(0.030)	(0.032)	(0.031)
Crafts/Processing (0/1)	-0.095***	-0.098***	-0.098***	-0.072**	-0.075**	-0.075**
	(0.020)	(0.023)	(0.022)	(0.030)	(0.033)	(0.032)
Services (0/1)	-0.103***	-0.106***	-0.105***	-0.081***	-0.085***	-0.084***
	(0.021)	(0.023)	(0.022)	(0.030)	(0.033)	(0.032)
Other activities (0/1)	-0.115***	-0.118***	-0.112***	-0.089***	-0.092***	-0.086**
	(0.025)	(0.027)	(0.026)	(0.033)	(0.036)	(0.034)
Av. Distance (ln, km) to city	0.005*	0.004	0.004	0.004	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

Motorized collect. transp (0/1)	-0.002	-0.001	-0.002	-0.003	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Av. Altitude (m)	0.000**	0.000*	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban (0/1)	0.010**	0.007	0.010*	0.011**	0.007	0.010*
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
Av. Household size	-0.012	-0.010	-0.012	-0.007	-0.004	-0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Av. # adults in HH	0.022*	0.019	0.022*	0.015	0.012	0.015
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
% of male HHH	-0.016	-0.020	-0.012	-0.017	-0.021*	-0.013
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)
Av. Age of HHH	-0.001*	-0.001	-0.001	-0.002***	-0.001*	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Av. literacy of HHH	-0.001	-0.002	-0.000	0.000	0.000	0.002
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)
Married monogamous (% HH)	0.016	0.017	0.015	0.022	0.022	0.020
	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)	(0.026)
Married polygamous (% HH)	0.004	-0.001	0.005	0.037	0.030	0.037
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)
Banked (% HH)	-0.015	-0.018	-0.014	0.000	-0.004	0.001
	(0.023)	(0.024)	(0.024)	(0.023)	(0.024)	(0.023)
No education (% HH)	0.010	0.014	0.012	-0.002	0.001	-0.001
	(0.035)	(0.035)	(0.035)	(0.034)	(0.035)	(0.035)
Primary education (% HH)	-0.008	0.004	-0.005	-0.006	0.007	-0.003
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Secondary educ. (% HH)	0.006	0.002	0.008	-0.000	-0.004	0.002
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Home tenant (% HH)	0.012	0.011	0.015	0.008	0.006	0.012
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
Walls - finished mat. (% HH)	-0.008	-0.008	-0.004	-0.008	-0.009	-0.005
	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)
Roof - finished mat. (% HH)	-0.014	-0.017	-0.019*	-0.006	-0.009	-0.011
	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)
Floor - finished mat. (% HH)	0.016	0.014	0.016	0.005	0.003	0.005
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Owns TV (% HH)	-0.030***	-0.029***	-0.030***	-0.027***	-0.026**	-0.027***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Owns iron (% HH)	0.003	-0.002	0.003	-0.007	-0.012	-0.007
	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)	(0.018)
Owns fridge (% HH)	0.036**	0.037**	0.032**	0.026*	0.027*	0.023
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Owns kitchen (% HH)	0.040**	0.042**	0.040**	0.049***	0.051***	0.049***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Owns computer (% HH)	-0.024	-0.017	-0.028	-0.019	-0.013	-0.023
	(0.023)	(0.024)	(0.023)	(0.023)	(0.023)	(0.022)
Owns decoder (% HH)	-0.017	-0.016	-0.012	-0.020	-0.020	-0.015
	(0.014)	(0.014)	(0.014)	(0.013)	(0.014)	(0.013)
Owns car (% HH)	0.036	0.037	0.036	0.036	0.037	0.036
	(0.026)	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
Demog. idio. shocks (% HH)	-0.024***	-0.025***	-0.022**	-0.024***	-0.024***	-0.022**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Natural cov. shocks (% HH)	-0.017*	-0.017	-0.019*	-0.027***	-0.027***	-0.029***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Econ. cov.shocks (% HH)	0.002	0.002	0.003	-0.005	-0.005	-0.004
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Econ. idio. Shocks (% HH)	-0.011	-0.014	-0.012	-0.016	-0.019	-0.017
	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
Violence cov. shocks (% HH)	-0.072***	-0.071***	-0.075***	-0.065***	-0.063***	-0.068***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Other cov. shocks (% HH)	0.013	0.002	0.026	0.009	-0.003	0.023
	(0.030)	(0.030)	(0.030)	(0.029)	(0.030)	(0.030)

Ratio rainfed/irrigated plots	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	5.273***	5.232***	5.231***	5.181***	5.171***	5.165***
	(0.00201)	(0.00237)	(0.00253)	(0.133)	(0.133)	(0.134)
Observations	129,740	129,670	129,687	135,001	134,933	134,947
District-product-unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
AR F-stat	0.000749	0.000802	0.000742	0.0121	0.0127	0.0119
KP Wald F-stat	67.23	47.24	65.34	72.76	55.51	68.18
LM-weak	47.52	31.70	29.50	43.24	29.68	26.83

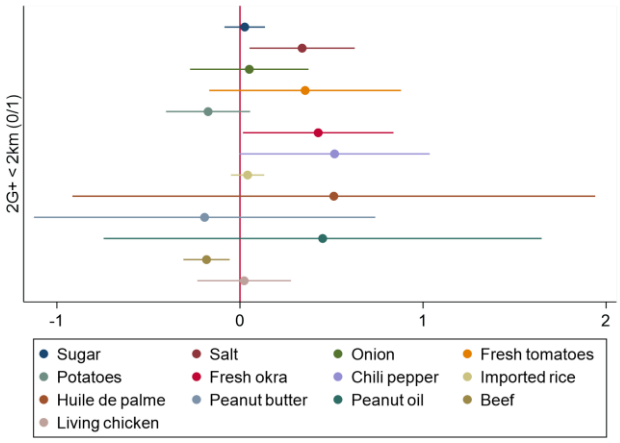
Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$..

B.2.3. 2SLS Estimation of Eq. (4), alternative FE calibrations.

Dep. Var: Ln $P_{z\,i}$ (record 1)	**(1)**	(2)	(3)	(4)	(5)	(6)	**(7)**
Dist. 2G+ <2km (0/1)	**0.116*** **	0.081***	0.097***	0.099***	0.061**	0.082**	**0.111*** **
	(0.018)	(0.017)	(0.022)	(0.021)	(0.028)	(0.034)	**(0.035)**
Controls	**No**	No	No	No	Yes	Yes	**Yes**
Product-unit FE	**Yes**	No	Yes	No	No	Yes	**No**
District FE	**No**	No	Yes	No	No	Yes	**No**
Region-product-unit FE	**No**	Yes	No	No	Yes	No	**No**
District-product-unit FE	**No**	No	No	Yes	No	No	**Yes**
Survey wave FE	**Yes**	Yes	Yes	Yes	Yes	Yes	**Yes**
Observations	**138,131**	137,586	138,131	132,910	134,381	134,933	**129,670**
AR F-stat	**8.93e-09**	5.85e-06	3.09e-05	1.14e-05	0.0341	0.0162	**0.0008**
KP Wald F-stat	**171.4**	133	102.6	89.97	74.81	54.55	**47.24**
LM-weak	**107.1**	81.84	59.49	63.24	36.61	29.61	**31.70**

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. When FEs are set at the region-product level, we control for the non-interacted network proximity dummy. The most flexible (col (1)) and most conservative approach (col (7)) are highlighted in bold.

B.2.4. Marginal effects of network connectivity on most traded product prices – product-level analysis.



Notes: 2SLS estimates of equation (4). 13 most-traded products in at least 7 of the 8 WAEMU member States, are reported. Standard errors robust to heteroskedasticity and clustered by EA.

B.3. Equation (6), 2SLS estimations, first and second-stage estimates.

	(1)	(2)	(3)	(4)
	2nd stage	1st stage	2nd stage	1st stage
Dep. Var:	CV price 1	2G+ cov (% district.)	CV price 2	2G+ cov (% district.)
2G+ coverage (% district.)	-0.518**		-0.510**	
	(0.205)		(0.206)	
IV - unweighted lightning risk		-0.003***		-0.003***

		(0.001)		(0.001)
Nighttime light density	0.023***	0.043***	0.023**	0.043***
	(0.009)	(0.002)	(0.009)	(0.002)
Population density	-0.000**	-0.000***	-0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Av. # of surveyed HHs	0.031***	-0.034***	0.031***	-0.034***
	(0.008)	(0.002)	(0.008)	(0.002)
Av. # of inhab. in EAs	-0.003	-0.004*	-0.003	-0.004*
	(0.004)	(0.002)	(0.004)	(0.002)
# EA (Ln)	0.009	0.027***	0.012	0.027***
	(0.009)	(0.004)	(0.009)	(0.004)
Elec. network (%district)	-0.001	-0.034***	-0.026*	-0.034***
	(0.016)	(0.010)	(0.016)	(0.010)
Water network (% district)	-0.041*	-0.087***	-0.034	-0.087***
	(0.022)	(0.010)	(0.022)	(0.010)
Av. Distance (ln, km) to city	-0.021***	-0.031***	-0.020***	-0.031***
	(0.008)	(0.003)	(0.008)	(0.003)
Motorized collect. transp (% dist)	-0.025**	-0.024***	-0.032**	-0.024***
	(0.013)	(0.007)	(0.013)	(0.007)
Urban (% EA)	-0.011	0.031***	-0.025	0.031***
	(0.017)	(0.010)	(0.017)	(0.010)
Av. Household size	0.037	0.141***	0.038	0.141***
	(0.042)	(0.021)	(0.041)	(0.021)
Av. # adults in HH	-0.049	-0.179***	-0.051	-0.179***
	(0.055)	(0.028)	(0.054)	(0.028)
% of male HHH	0.055	0.007	0.045	0.007
	(0.044)	(0.027)	(0.044)	(0.027)
Av. Age of HHH	0.008**	0.013***	0.008**	0.013***
	(0.003)	(0.002)	(0.003)	(0.002)
Av. literacy of HHH	0.080***	0.047***	0.058**	0.047***
	(0.027)	(0.016)	(0.026)	(0.016)
Married monogamous (% HH)	-0.041	0.168***	-0.006	0.168***
	(0.092)	(0.053)	(0.093)	(0.053)
Married polygamous (% HH)	-0.250**	0.005	-0.236**	0.005
	(0.098)	(0.053)	(0.098)	(0.053)
Banked. (% HH)	0.119	0.235***	0.102	0.235***
	(0.094)	(0.049)	(0.093)	(0.049)
No education. (% HH)	-0.321	-1.017***	-0.456*	-1.017***
	(0.254)	(0.119)	(0.255)	(0.119)
Primary education (% HH)	-0.394	-1.065***	-0.508*	-1.065***
	(0.270)	(0.120)	(0.272)	(0.120)
Secondary ed. (% HH)	0.009	-0.176	-0.146	-0.176
	(0.197)	(0.139)	(0.195)	(0.139)
Av. tot. HH spending (XOF, ln)	0.114***	0.072***	0.101***	0.072***
	(0.023)	(0.012)	(0.023)	(0.012)
Home tenant (% HH)	-0.041	-0.137***	-0.039	-0.137***
	(0.048)	(0.024)	(0.047)	(0.024)
Walls - finished mat. (% HH)	0.051**	-0.056***	0.055**	-0.056***
	(0.024)	(0.012)	(0.023)	(0.012)
Roof - finished mat. (% HH)	-0.063**	-0.024	-0.048*	-0.024
	(0.027)	(0.016)	(0.026)	(0.016)
Floor - finished mat. (% HH)	0.020	0.162***	0.028	0.162***
	(0.041)	(0.017)	(0.040)	(0.017)
Owns TV (% HH)	0.092**	0.118***	0.123***	0.118***
	(0.047)	(0.029)	(0.046)	(0.029)
Owns iron (% HH)	-0.021	0.053	-0.072	0.053
	(0.079)	(0.062)	(0.077)	(0.062)
Owns fridge (% HH)	-0.239***	-0.238***	-0.230***	-0.238***
	(0.084)	(0.044)	(0.085)	(0.044)
Owns kitchen (% HH)	-0.266	-0.781***	-0.250	-0.781***

	(0.185)	(0.050)	(0.185)	(0.050)
Owns computer (% HH)	-0.132	0.125	-0.151	0.125
	(0.133)	(0.087)	(0.132)	(0.087)
Owns decoder (% HH)	-0.053	-0.069**	-0.031	-0.069**
	(0.053)	(0.033)	(0.051)	(0.033)
Owns car (% HH)	0.200	0.307***	0.182	0.307***
	(0.166)	(0.116)	(0.168)	(0.116)
Demog. idio. shocks (% HH)	-0.138*	-0.314***	-0.151**	-0.314***
	(0.073)	(0.016)	(0.072)	(0.016)
Natural cov. shocks (% HH)	-0.064**	-0.127***	-0.044	-0.127***
	(0.029)	(0.012)	(0.029)	(0.012)
Econ. cov.shocks (% HH)	-0.140**	-0.253***	-0.138**	-0.253***
	(0.057)	(0.012)	(0.056)	(0.012)
Econ. idio. Shocks (% HH)	0.023	0.192***	0.045	0.192***
	(0.055)	(0.024)	(0.055)	(0.024)
Violence cov. shocks (% HH)	-0.111	-0.350***	-0.096	-0.350***
	(0.082)	(0.023)	(0.082)	(0.023)
Other cov. shocks (% HH)	0.104	0.440***	0.096	0.440***
	(0.115)	(0.043)	(0.114)	(0.043)
Av. Ratio rainfed / irrigated surfaces	0.000	-0.000***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Observations	19,399	19,399	19,399	19,399
AR F-stat	0.00598		0.00694	
KP Wald F-stat	41.82		41.82	
LM-weak	41.51		41.51	

Standard errors in brackets, robust to heteroskedasticity and clustered by region-product. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.4. Mobile connectivity and households spending, equation (7).

B.4.1. Mobile connectivity and total expenditures per HH member.

Dep. Var.: total spending /HH member (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6) Urban	(7) Rural
Distance 2G+ (ln, km) x # mob.	-0.072***						
	(0.015)						
Distance 2G+ <2km (0/1) x # mob.		0.178***	0.205***	0.190***	0.174***	0.125**	0.637***
		(0.035)	(0.041)	(0.045)	(0.038)	(0.054)	(0.231)
Distance 2G+ <2km (0/1)	-	-	-0.382***	0.041	-0.403***	-	-
	-	-	(0.109)	(0.174)	(0.137)	-	-
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EA controls	No	No	No	Yes	Yes	No	No
EA FEs	Yes	Yes	No	No	No	Yes	Yes
District FEs	No	No	No	No	Yes	No	No
Survey wave FEs	Yes	Yes	No	No	Yes	Yes	Yes
Observations	56,829	56,817	56,817	55,466	55,466	23,220	33,597
Anderson-Rub. F-test (p-val.)	9.18e-08	9.23e-08	2.60e-06	8.18e-06	8.57e-09	0.0244	5.48e-08
KP Wald F-stat	66.36	99.72	41.50	16.39	14.74	47.45	11.54
KP rank LM-stat	53.38	65.50	62.35	21.36	20.14	21.16	9.357

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.4.2. Mobile connectivity and Non-food expenditures per HH member.

Dep. Var.: Non food spending /HH member (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6) Urban	(7) Rural
Distance 2G+ (ln, km) x # mob.	-0.026**						
	(0.012)						

Distance 2G+ <2km (0/1) x # mob.		0.064**	0.127***	0.107***	0.066**	0.017	0.339**
		(0.030)	(0.033)	(0.039)	(0.029)	(0.045)	(0.150)
Distance 2G+ <2km (0/1)	-	-	0.110	0.458**	-0.157	-	-
	-	-	(0.099)	(0.197)	(0.128)	-	-
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EA controls	No	No	No	Yes	Yes	No	No
EA FEs	Yes	Yes	No	No	No	Yes	Yes
District FEs	No	No	No	No	Yes	No	No
Survey wave FEs	Yes	Yes	No	No	Yes	Yes	Yes
Observations	56,829	56,817	56,817	55,466	55,466	23,220	33,597
Anderson-Rub. F-test (p-val.)	0.0274	0.0279	6.83e-07	7.83e-06	0.0340	0.701	0.00110
KP Wald F-stat	68.20	101.3	42.79	16.42	14.87	47.47	11.83
KP rank LM-stat	55.18	66.89	65.05	21.30	20.18	21.20	9.571

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01.

B.4.3. Mobile connectivity and expenditures per HH member, controlling for HH farm sales.

Dep. Var.: Exp /HH member (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Total sample			Urban			Rural	
	Total	Food	Non food	Total	Food	Non food	Total	Food	Non food
Dist. 2G+ <2km (0/1) x nb. Tel	0.715***	0.467**	0.353**	0.218***	0.125	0.113	0.987*	0.658*	0.480*
	(0.266)	(0.200)	(0.164)	(0.084)	(0.079)	(0.087)	(0.509)	(0.371)	(0.287)
HH farm sales (XOF, ln)	0.008***	0.005***	0.004***	0.006***	0.003	0.004**	0.008***	0.006***	0.004***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,006	31,006	31,006	5,001	5,001	5,001	26,005	26,005	26,005
AR F-test (p-val.)	8.46e-08	0.000229	0.00515	0.00207	0.114	0.161	1.89e-06	0.000661	0.0128
KP Wald F-stat	10.40	10.70	10.54	16.35	16.77	16.29	4.890	5.019	4.944
KP rank LM-stat	8.271	8.497	8.362	10.80	11	10.78	4.122	4.225	4.161

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01.

B.5. Mobile connectivity and food diversity

B.5.1. Mobile connectivity and consumed food diversity: 2SLS estimations.

Dep. Var.: # consumed prod.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All HHs			Urban HHs			Rural HHs	
(A) Dist. 2G+ (ln, km) × # mob.	-0.782***			-0.973***			-1.964		
	(0.186)			(0.325)			(1.340)		
(B) Dist. 2G+ <2km (0/1) × # mob.		1.947***	1.630***		2.560***	1.347*		3.179**	2.860**
		(0.443)	(0.410)		(0.822)	(0.803)		(1.514)	(1.347)
(C) Dist. 2G+ <2km (0/1)			-5.015***			-2.944			-4.610*
			(1.395)			(2.655)			(2.367)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EA FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
District FE	No	No	Yes	No	No	Yes	No	No	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,829	56,817	56,817	23,220	23,220	23,220	33,609	33,597	33,597
AR. F-test (p-val.)	1.86e-05	1.80e-05	1.43e-05	0.00137	0.00137	0.228	0.0218	0.0213	0.0733
KP Wald F-stat	64.12	97.65	52.73	28.63	47.25	25.02	2.846	11.18	6.036

KP rank LM-stat	52.33	65.08	65.40	22.17	21.10	19.35	2.644	9.134	10.15

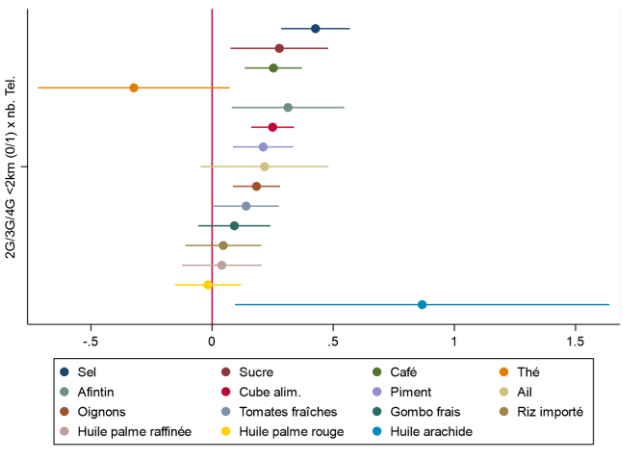
Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01. Reported first-stage statistics robust to heteroskedasticity and clustering. The number of self-consumed commodities is included as control. The dependent variable is the number of different commodities consumed by the household in the 7 days preceding the survey.

B.5.2. Mobile connectivity and self-consumed food product diversity, 2SLS estimates.

Dep. Var.: # self-consumed commodities	(1)	(2)	(3)	(4)	(5)	(6)
	All HHs		Urban HHs		Rural HHs	
Distance 2G+ (ln, km) × # mob.	0.706***		0.504***		2.877*	
	(0.115)		(0.136)		(1.665)	
Distance 2G+ <2km (0/1) × # mob.		-1.755***		-1.324***		-4.688***
		(0.258)		(0.355)		(1.426)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA Fes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave Fes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,829	56,817	23,220	23,220	33,609	33,597
Anderson-Rub. F-test (p-val.)	0.0000	0.0000	0.0005	0.0005	4.09e-08	4.14e-08
KP Wald F-stat	66.36	99.72	28.90	47.45	3.017	11.54
KP rank LM-stat	53.37	65.50	22.45	21.17	2.792	9.357

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01. Reported first-stage statistics robust to heteroskedasticity and clustering. The dependent variable is the number of different commodities self-consumed by the household in the 7 days preceding the survey.

B.6. Marginal effects of mobile connectivity on quantities of commodities consumed per HH member - product level analysis.



Notes: 2SLS estimates of equation (7). 15 most-consumed products in at least 7 of the 8 WAEMU member states are considered. Dependent variable: quantities of consumed commodities per HH member (grams, ln).

B.7. Mobile connectivity and quantities of food purchased by households, equation (7).

Dep. Var.: quantities of purchased commodity / HH member (grams, ln)	(1)	(2)	(3)	(4)	(5)	(6)
			Urban		Rural	
Distance 2G+ (ln, km) x # mob.	-0.111***		-0.116***		-0.262***	
	(0.011)		(0.017)		(0.054)	
Distance 2G+ <2km (0/1) x # mob..		0.288***		0.295***		0.610***

		(0.026)		(0.044)		(0.108)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Commodity-product FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	757,895	757,790	415,375	415,375	342,126	342,021
Anderson-Rub. F-test (p-val.)	0	0	1.44e-10	1.44e-10	0	0
KP Wald F-stat	263.4	336.3	110.5	144.3	34.25	54.06
KP rank LM-stat	240.3	254	99.17	81.49	32.69	48.44

Standard errors in brackets, robust to heteroskedasticity and clustered by HH. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Reported first-stage statistics robust to heteroskedasticity and clustering.

C. C. Handling non-standard measurement units

C.1. Treatment of non-standard measurement unit conversion factors.

Several modules in the EHCVM 2018-2019 WAEMU surveys used in this study, including consumer prices recorded at the enumeration area level (Section 5: Recording consumption prices), household-level food consumption (Section 7: Part B: Food consumed within household), and household-level agricultural crop production (Section 16: Agriculture, Part C: Crops), contain information about food commodities reported in non-standard measurement units. Some of these units have common names across countries and regions (ex. large, medium, or small sack of maize), but the weight in grams of a given unit can differ from one district to the next. Other units are unique to a given country, region, or commodity.

The EHCVM surveys include individual country-specific databases of conversion factors for non-standard measurement units, providing weight in grams of each commodity-unit pair. In six of the eight countries, these factors are provided at the regional level (the second administrative division in most countries and the third administrative division in Côte d'Ivoire). For Côte d'Ivoire and Sénégal, district-level conversion factors were provided, but the district names in these databases were not the same as those in the main EHCVM modules, so we collapsed the data to the regional level. In Benin and Togo, the conversion factors are provided at the district level (the third administrative division). Within a given administrative division, conversion factors are provided for a given agricultural commodity, unit of measurement, size of unit of measurement, and urban or rural strata.

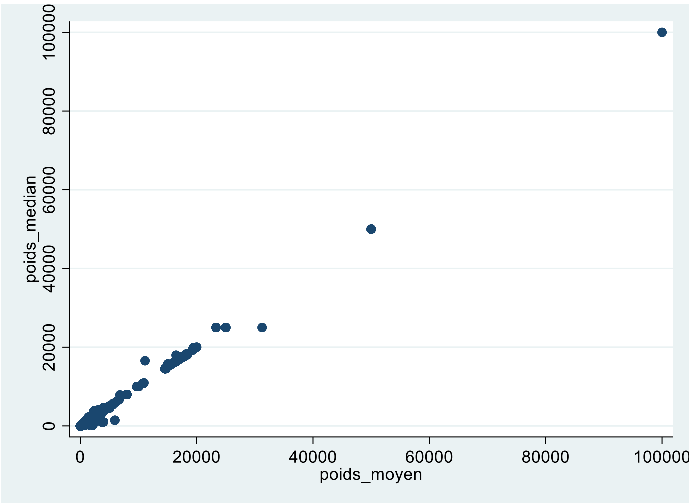
To use these conversion factors, we first examined each country-specific conversion factor databases and ensured that the commodity names, unit names, and unit sizes correspond exactly with those in the Section 5, 7B, and 16C databases. To do this, we converted all merging variables into character form and ensured that spelling and case-sensitivity of all variable names, commodity names, and measurement unit names were identical between the conversion factor databases and the Section 5, 7B, and 16C databases.

The next step involved merging each of the three databases (Sections 5, 7B, and 16C) with the eight country-specific conversion factor databases. Conversion factors were expressed either in median weight in grams (Guinea-Bissau, Burkina Faso, Niger), average weight in grams (Burkina Faso, Mali, Togo) or unspecified weight in grams (Benin Côte d'Ivoire, Senegal). Given the very high level of correlation between median and average weights in Burkina Faso (99.6%, see Appendix C.1), we assume that the same correlation holds in other WAEMU countries and use each weight as if it were the same metric in all countries (applying the median weight in Burkina Faso, where the two metrics are available).

In the Section 5, 7B, and 16C databases, some of the commodity-measurement unit combinations had available factors in the conversion factor database for the district or region in which they were located, whereas other observations did not have a conversion factor. For each of the Section 5, 7B, and 16C databases, we first created restricted databases that included only observations for which a conversion factor was available in the local area (department or region). We then created imputed databases with varying levels of imputation – applying the mean commodity-measurement unit conversion factors at the district, region, and country levels for those observations that did not have a conversion factor available. This gave us four separate databases – a restricted database and three imputed databases with different aggregation levels of imputed mean conversion factors.

After the conversion factor merging and imputation was complete, we also created a district-level database of food commodities (module 5) by collapsing the EA-level database on converted food price to obtain district averages of food prices in XOF, standard deviation, and standard error of prices of each food commodity traded across the various enumeration areas within a given district.

C.2. Correlation between average and median conversion factors for quantities of food consumed by households in Burkina Faso.



Correlation coefficient

	Median weight	Average weight
Median weight	1	
Average weight	0.9967	1

D. D. Additional estimations

D.1. The effect of internet connectivity on the demand for food products.

D.1.1. Internet connectivity and total expenditure per HH member

Dep; var: Total exp / HH member (XOF, ln)	(1) Total survey	(2)	(3) Urban EAs	(4)	(5) Rural EAs	(6)
Distance 2G+ (ln, km) x Int.	-0.068**		-0.015		-0.210	
	(0.030)		(0.034)		(0.138)	
Distance 2G+ <2km (0/1) x Int.		0.172**		0.039		0.434*
		(0.074)		(0.092)		(0.231)
Uses internet	0.152***	-0.028	0.103***	0.063	0.429*	-0.104
	(0.028)	(0.051)	(0.016)	(0.082)	(0.226)	(0.104)
# mobile phones in HH	0.051***	0.051***	0.040***	0.040***	0.068***	0.068***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Household size	-0.127***	-0.127***	-0.122***	-0.122***	-0.138***	-0.138***
	(0.005)	(0.005)	(0.008)	(0.008)	(0.006)	(0.006)
# adults-equiv. FAO	0.061***	0.061***	0.043***	0.043***	0.079***	0.080***
	(0.006)	(0.006)	(0.010)	(0.010)	(0.008)	(0.008)
HH gender (0/1)	-0.100***	-0.100***	-0.068***	-0.068***	-0.120***	-0.119***
	(0.008)	(0.008)	(0.012)	(0.012)	(0.011)	(0.011)
Age of HH	-0.001**	-0.001**	-0.000	-0.000	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Literacy of HH (0/1)	0.044***	0.044***	0.064***	0.064***	0.030***	0.030***
	(0.008)	(0.008)	(0.013)	(0.013)	(0.010)	(0.010)
Married monogamous (0/1)	-0.157***	-0.156***	-0.158***	-0.158***	-0.149***	-0.147***
	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
Married polygamous (0/1)	-0.040***	-0.040***	-0.036**	-0.036**	-0.044***	-0.043***
	(0.011)	(0.011)	(0.016)	(0.016)	(0.015)	(0.015)
Banked (0/1)	0.475***	0.476***	0.473***	0.473***	0.438***	0.446***
	(0.015)	(0.015)	(0.021)	(0.021)	(0.026)	(0.022)
No education (0/1)	-0.068***	-0.067***	-0.044***	-0.044***	-0.102***	-0.092***
	(0.012)	(0.012)	(0.016)	(0.016)	(0.034)	(0.028)
Primary education (0/1)	-0.072***	-0.071***	-0.068***	-0.068***	-0.095***	-0.085***
	(0.012)	(0.012)	(0.014)	(0.014)	(0.033)	(0.027)
Secondary ed. 1 (0/1)	-0.084***	-0.084***	-0.073***	-0.073***	-0.111***	-0.104***
	(0.012)	(0.012)	(0.013)	(0.013)	(0.033)	(0.028)
Secondary ed. 2 (0/1)	-0.061***	-0.060***	-0.064***	-0.064***	-0.043	-0.039
	(0.014)	(0.014)	(0.017)	(0.017)	(0.030)	(0.028)
Uses electric network (0/1)	0.105***	0.105***	0.111***	0.111***	0.071***	0.075***
	(0.010)	(0.010)	(0.015)	(0.015)	(0.018)	(0.016)
Uses solar elec./group elec. (0/1)	0.081***	0.081***	0.052***	0.052***	0.081***	0.081***
	(0.009)	(0.009)	(0.018)	(0.018)	(0.010)	(0.010)
Improved waste disposal (0/1)	0.043***	0.043***	0.056***	0.055***	0.031**	0.031**
	(0.009)	(0.009)	(0.012)	(0.012)	(0.015)	(0.014)
Improved toiled (0/1)	0.046***	0.047***	0.047***	0.047***	0.036**	0.038***
	(0.008)	(0.008)	(0.010)	(0.010)	(0.014)	(0.014)
Improved human waste disposal (0/1)	0.043***	0.043***	0.035***	0.035***	0.049***	0.051***
	(0.009)	(0.009)	(0.011)	(0.011)	(0.015)	(0.014)
Improved sewage disposal (0/1)	0.054***	0.054***	0.058***	0.058***	0.030	0.033
	(0.011)	(0.011)	(0.012)	(0.012)	(0.026)	(0.025)
Demographic idiosync. shocks	0.044***	0.043***	0.031***	0.031***	0.052***	0.051***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Natural covariant shocks	0.023***	0.024***	0.023*	0.023*	0.016*	0.019**
	(0.007)	(0.007)	(0.013)	(0.013)	(0.009)	(0.009)
Economic covariant shocks	0.001	0.001	-0.006	-0.006	0.008	0.006
	(0.007)	(0.007)	(0.010)	(0.010)	(0.009)	(0.009)

Economic idiosync. shocks	0.034***	0.034***	0.035***	0.035***	0.033***	0.032***
	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
Violence covariant shocks	0.047***	0.047***	0.035	0.035	0.052***	0.051***
	(0.017)	(0.017)	(0.027)	(0.027)	(0.020)	(0.020)
Other covariant shocks	0.023	0.022	0.060	0.060	0.007	0.002
	(0.022)	(0.022)	(0.044)	(0.044)	(0.024)	(0.022)
Rainfed/irrigated surface area ratio	-0.000	-0.000	-0.000**	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total plot area (ha)	-0.000**	-0.000**	0.000**	0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rents land	-0.015*	-0.016*	-0.045***	-0.045***	0.014	0.016
	(0.009)	(0.009)	(0.010)	(0.010)	(0.021)	(0.019)
Walls - finished materials (0/1)	0.045***	0.046***	0.073***	0.073***	0.038***	0.038***
	(0.010)	(0.010)	(0.017)	(0.017)	(0.011)	(0.011)
Roof - finished materials (0/1)	0.058***	0.057***	0.069***	0.069***	0.055***	0.054***
	(0.010)	(0.010)	(0.026)	(0.026)	(0.011)	(0.011)
Floor - finished material (0/1)	0.081***	0.081***	0.089***	0.089***	0.076***	0.076***
	(0.009)	(0.009)	(0.017)	(0.017)	(0.010)	(0.010)
TV (0/1)	0.086***	0.086***	0.082***	0.082***	0.095***	0.097***
	(0.008)	(0.008)	(0.011)	(0.011)	(0.013)	(0.013)
Has iron (0/1)	0.110***	0.112***	0.117***	0.118***	0.072*	0.083**
	(0.015)	(0.014)	(0.016)	(0.016)	(0.038)	(0.035)
Has fridge (0/1)	0.133***	0.133***	0.151***	0.151***	0.085***	0.085***
	(0.010)	(0.010)	(0.011)	(0.011)	(0.023)	(0.021)
Has kitchen (0/1)	0.093***	0.093***	0.083***	0.084***	0.159***	0.151***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.036)	(0.034)
Owns computer (0/1)	0.077***	0.078***	0.099***	0.099***	0.013	0.019
	(0.013)	(0.013)	(0.014)	(0.014)	(0.045)	(0.038)
Owns decoder (0/1)	0.089***	0.089***	0.108***	0.108***	0.064***	0.064***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.016)	(0.016)
Owns car (0/1)	0.379***	0.379***	0.385***	0.385***	0.382***	0.383***
	(0.015)	(0.015)	(0.017)	(0.017)	(0.039)	(0.037)
Observations	56,829	56,817	23,220	23,220	33,609	33,597
R-squared	0.461	0.463	0.565	0.565	0.355	0.377
AR F-stat	0.0142	0.0142	0.671	0.671	0.0181	0.0182
KP Wald F-stat (p-val)	61.30	92.60	31.51	50.10	5.040	13.15
LM-weak	30.32	44.46	11.87	14.62	3.920	9.587

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$..

D.1.2. Internet connectivity and food expenditure per HH member

Dep; var: Food exp / HH member (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)
	Total survey		Urban EAs		Rural EAs	
Distance 2G+ (ln, km) x Int.	-0.078**		-0.052		-0.207	
	(0.031)		(0.042)		(0.140)	
Distance 2G+ <2km (0/1) x Int.		0.198***		0.137		0.429*
		(0.076)		(0.112)		(0.234)
Uses internet	0.096***	-0.113**	0.034*	-0.106	0.370	-0.157
	(0.031)	(0.053)	(0.018)	(0.100)	(0.231)	(0.103)
# mobile phones in HH	0.023***	0.023***	0.020***	0.020***	0.033***	0.032***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Non-food exp. (XOF, ln)	0.267***	0.266***	0.279***	0.279***	0.263***	0.262***
	(0.008)	(0.008)	(0.014)	(0.014)	(0.010)	(0.010)
Household size	-0.134***	-0.135***	-0.133***	-0.133***	-0.141***	-0.141***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.007)	(0.007)
Education of HH	0.062***	0.062***	0.049***	0.049***	0.076***	0.077***
	(0.007)	(0.007)	(0.011)	(0.011)	(0.010)	(0.010)
HH gender (0/1)	-0.095***	-0.095***	-0.096***	-0.096***	-0.090***	-0.088***
	(0.009)	(0.009)	(0.014)	(0.014)	(0.013)	(0.013)
Age of HH	-0.001***	-0.001***	-0.002***	-0.002***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Literacy of HH (0/1)	0.019**	0.019**	0.026*	0.026*	0.012	0.012
	(0.009)	(0.009)	(0.016)	(0.016)	(0.011)	(0.011)
Married monogamous (0/1)	-0.219***	-0.219***	-0.215***	-0.215***	-0.217***	-0.215***
	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)	(0.013)
Married polygamous (0/1)	-0.130***	-0.129***	-0.101***	-0.101***	-0.146***	-0.145***
	(0.013)	(0.013)	(0.019)	(0.019)	(0.017)	(0.017)
Banked (0/1)	0.363***	0.364***	0.376***	0.377***	0.309***	0.317***
	(0.016)	(0.016)	(0.024)	(0.024)	(0.027)	(0.024)
No education (0/1)	-0.001	0.001	0.016	0.016	-0.030	-0.021
	(0.018)	(0.018)	(0.025)	(0.025)	(0.035)	(0.030)
Primary education (0/1)	-0.012	-0.012	0.011	0.011	-0.047	-0.037
	(0.016)	(0.016)	(0.019)	(0.019)	(0.034)	(0.029)
Secondary ed. 1 (0/1)	-0.032**	-0.032**	-0.014	-0.014	-0.064*	-0.057*
	(0.016)	(0.016)	(0.019)	(0.019)	(0.034)	(0.030)
Secondary ed. 2 (0/1)	-0.024	-0.023	-0.024	-0.023	-0.016	-0.013
	(0.019)	(0.019)	(0.024)	(0.024)	(0.034)	(0.032)
Uses electric network (0/1)	0.007	0.007	0.001	0.001	-0.015	-0.012
	(0.012)	(0.012)	(0.017)	(0.017)	(0.020)	(0.018)
Uses solar elec./group elec. (0/1)	0.016*	0.016*	-0.022	-0.022	0.022**	0.022**
	(0.010)	(0.010)	(0.022)	(0.022)	(0.011)	(0.011)
Improved waste disposal (0/1)	0.037***	0.037***	0.038**	0.037**	0.039**	0.038**
	(0.011)	(0.011)	(0.016)	(0.016)	(0.016)	(0.016)
Improved toiled (0/1)	0.021**	0.021**	0.007	0.008	0.030*	0.033**
	(0.010)	(0.010)	(0.013)	(0.013)	(0.016)	(0.015)
Improved human waste disposal (0/1)	0.010	0.010	-0.002	-0.002	0.021	0.024*
	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)	(0.014)
Improved sewage disposal (0/1)	0.030**	0.031**	0.031**	0.032**	0.025	0.028
	(0.013)	(0.013)	(0.015)	(0.015)	(0.033)	(0.031)
Demographic idiosync. shocks	-0.005	-0.005	-0.016	-0.016	0.003	0.002
	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)
Natural covariant shocks	0.011	0.012	0.002	0.003	0.008	0.011
	(0.009)	(0.009)	(0.014)	(0.013)	(0.011)	(0.010)
Economic covariant shocks	-0.001	-0.001	0.007	0.007	-0.002	-0.004
	(0.008)	(0.008)	(0.011)	(0.011)	(0.010)	(0.010)
Economic idiosync. shocks	0.020**	0.019**	0.032***	0.032***	0.008	0.007

	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
Violence covariant shocks	0.011	0.011	0.008	0.008	0.015	0.014
	(0.018)	(0.018)	(0.032)	(0.032)	(0.022)	(0.021)
Other covariant shocks	0.023	0.022	0.028	0.028	0.027	0.021
	(0.020)	(0.019)	(0.033)	(0.033)	(0.025)	(0.023)
Rainfed/irrigated surface area ratio	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total plot area (ha)	-0.000**	-0.000**	0.000	0.000	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rents land	0.047***	0.046***	0.023**	0.022*	0.049**	0.051**
	(0.010)	(0.010)	(0.012)	(0.011)	(0.025)	(0.023)
Walls - finished materials (0/1)	0.003	0.003	0.004	0.004	0.003	0.003
	(0.011)	(0.011)	(0.020)	(0.020)	(0.013)	(0.013)
Roof - finished materials (0/1)	0.018	0.018	0.003	0.002	0.020	0.019
	(0.011)	(0.011)	(0.027)	(0.027)	(0.013)	(0.013)
Floor - finished material (0/1)	0.036***	0.036***	0.042**	0.041**	0.033***	0.032***
	(0.010)	(0.010)	(0.019)	(0.019)	(0.012)	(0.012)
TV (0/1)	0.008	0.008	0.005	0.005	0.013	0.015
	(0.010)	(0.010)	(0.013)	(0.013)	(0.015)	(0.015)
Has iron (0/1)	0.057***	0.058***	0.074***	0.075***	-0.046	-0.034
	(0.017)	(0.017)	(0.018)	(0.018)	(0.044)	(0.043)
Has fridge (0/1)	0.011	0.011	0.023*	0.023*	0.000	0.000
	(0.012)	(0.012)	(0.014)	(0.014)	(0.027)	(0.025)
Has kitchen (0/1)	0.022	0.022	0.027	0.027	0.020	0.012
	(0.018)	(0.018)	(0.018)	(0.018)	(0.050)	(0.049)
Owns computer (0/1)	0.013	0.013	0.018	0.018	0.009	0.015
	(0.016)	(0.016)	(0.017)	(0.017)	(0.048)	(0.043)
Owns decoder (0/1)	0.026**	0.026**	0.037***	0.037***	0.010	0.010
	(0.010)	(0.010)	(0.012)	(0.012)	(0.020)	(0.020)
Owns car (0/1)	0.009	0.009	0.011	0.011	0.000	0.001
	(0.019)	(0.019)	(0.022)	(0.022)	(0.043)	(0.040)
Observations	56,829	56,817	23,220	23,220	33,609	33,597
R-squared	0.341	0.343	0.411	0.411	0.273	0.291
AR F-stat (p-val)	0.00691	0.00691	0.218	0.218	0.0218	0.0218
KP Wald F-stat	61.30	92.61	31.46	50.10	5.039	13.14
LM-weak	30.32	44.46	11.85	14.61	3.919	9.585

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01..

D.1.3. Internet and non-food expenditure per HH member

Dep. Var.: Non-food exp /HH member (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)
	Total survey		Urban EAs		Rural EAs	
Distance 2G+ (ln, km) x Int.	-0.044		0.030		-0.216	
	(0.034)		(0.034)		(0.149)	
Distance 2G+ <2km (0/1) x Int.		0.112		-0.080		6.378*
		(0.087)		(0.089)		(3.495)
Uses internet	0.138***	0.020	0.095***	0.177**	0.453*	-2.665*
	(0.033)	(0.061)	(0.016)	(0.079)	(0.245)	(1.529)
# mobile phones in HH	0.059***	0.059***	0.040***	0.040***	0.082***	0.078***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.010)
Food expenses (XOF, ln)	0.227***	0.227***	0.201***	0.201***	0.240***	0.226***
	(0.007)	(0.007)	(0.012)	(0.012)	(0.009)	(0.020)
Household size	-0.133***	-0.133***	-0.128***	-0.128***	-0.143***	-0.149***
	(0.005)	(0.005)	(0.009)	(0.009)	(0.006)	(0.014)
Education of HH	0.038***	0.038***	0.026**	0.026**	0.053***	0.060***
	(0.007)	(0.007)	(0.011)	(0.011)	(0.009)	(0.020)
HH gender (0/1)	-0.087***	-0.087***	-0.055***	-0.055***	-0.109***	-0.168***

	(0.010)	(0.010)	(0.014)	(0.014)	(0.015)	(0.044)
Age of HH	-0.001***	-0.001***	-0.000	-0.000	-0.001***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Literacy of HH (0/1)	0.047***	0.047***	0.077***	0.077***	0.025**	0.005
	(0.008)	(0.008)	(0.015)	(0.015)	(0.010)	(0.026)
Married monogamous (0/1)	-0.153***	-0.154***	-0.158***	-0.158***	-0.145***	-0.170***
	(0.010)	(0.010)	(0.014)	(0.014)	(0.015)	(0.032)
Married polygamous (0/1)	-0.039***	-0.039***	-0.039**	-0.039**	-0.042***	-0.067*
	(0.012)	(0.012)	(0.018)	(0.018)	(0.016)	(0.035)
Banked (0/1)	0.540***	0.541***	0.527***	0.527***	0.519***	0.445***
	(0.018)	(0.018)	(0.025)	(0.025)	(0.032)	(0.105)
No education (0/1)	-0.108***	-0.107***	-0.074***	-0.075***	-0.147***	-0.246
	(0.014)	(0.014)	(0.019)	(0.019)	(0.038)	(0.164)
Primary education (0/1)	-0.102***	-0.102***	-0.113***	-0.114***	-0.115***	-0.207
	(0.013)	(0.013)	(0.016)	(0.016)	(0.036)	(0.160)
Secondary ed. 1 (0/1)	-0.099***	-0.099***	-0.095***	-0.096***	-0.117***	-0.133
	(0.013)	(0.013)	(0.015)	(0.015)	(0.036)	(0.156)
Secondary ed. 2 (0/1)	-0.077***	-0.076***	-0.081***	-0.082***	-0.057*	0.111
	(0.017)	(0.018)	(0.020)	(0.020)	(0.035)	(0.164)
Uses electric network (0/1)	0.150***	0.150***	0.167***	0.167***	0.108***	-0.017
	(0.011)	(0.011)	(0.016)	(0.016)	(0.019)	(0.086)
Uses solar elec./group elec. (0/1)	0.100***	0.100***	0.085***	0.085***	0.092***	0.100***
	(0.009)	(0.009)	(0.019)	(0.019)	(0.011)	(0.026)
Improved waste disposal (0/1)	0.026***	0.026***	0.046***	0.046***	0.008	0.027
	(0.009)	(0.009)	(0.011)	(0.012)	(0.015)	(0.038)
Improved toiled (0/1)	0.052***	0.052***	0.065***	0.065***	0.025	0.006
	(0.009)	(0.009)	(0.011)	(0.011)	(0.016)	(0.048)
Improved human waste disposal (0/1)	0.056***	0.056***	0.053***	0.053***	0.053***	0.046
	(0.009)	(0.009)	(0.011)	(0.011)	(0.017)	(0.046)
Improved sewage disposal (0/1)	0.056***	0.056***	0.065***	0.065***	0.014	-0.127
	(0.013)	(0.013)	(0.014)	(0.014)	(0.024)	(0.105)
Demographic idiosync. shocks	0.061***	0.061***	0.051***	0.051***	0.067***	0.077***
	(0.006)	(0.006)	(0.009)	(0.009)	(0.009)	(0.020)
Natural covariant shocks	0.016**	0.017**	0.030**	0.030**	0.004	-0.014
	(0.007)	(0.007)	(0.015)	(0.015)	(0.009)	(0.021)
Economic covariant shocks	-0.004	-0.004	-0.026**	-0.026**	0.011	0.048
	(0.007)	(0.007)	(0.012)	(0.012)	(0.010)	(0.030)
Economic idiosync. shocks	0.036***	0.036***	0.026**	0.026**	0.048***	0.062**
	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)	(0.030)
Violence covariant shocks	0.063***	0.063***	0.038	0.038	0.070***	0.098**
	(0.017)	(0.017)	(0.026)	(0.026)	(0.021)	(0.043)
Other covariant shocks	0.017	0.017	0.087*	0.087*	-0.017	0.076
	(0.026)	(0.026)	(0.052)	(0.052)	(0.028)	(0.088)
Rainfed/irrigated surface area ratio	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total plot area (ha)	-0.000	-0.000	0.000**	0.000**	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rents land	-0.038***	-0.038***	-0.071***	-0.071***	0.009	-0.155
	(0.010)	(0.010)	(0.011)	(0.011)	(0.022)	(0.128)
Walls - finished materials (0/1)	0.069***	0.069***	0.108***	0.108***	0.059***	0.059***
	(0.009)	(0.009)	(0.017)	(0.017)	(0.010)	(0.020)
Roof - finished materials (0/1)	0.075***	0.075***	0.116***	0.116***	0.067***	0.110***
	(0.011)	(0.011)	(0.026)	(0.026)	(0.012)	(0.037)
Floor - finished material (0/1)	0.098***	0.098***	0.107***	0.107***	0.091***	0.107***
	(0.009)	(0.009)	(0.017)	(0.017)	(0.010)	(0.029)
TV (0/1)	0.111***	0.111***	0.102***	0.102***	0.122***	0.123***
	(0.009)	(0.009)	(0.012)	(0.012)	(0.015)	(0.044)
Has iron (0/1)	0.102***	0.103***	0.102***	0.102***	0.125***	0.163
	(0.015)	(0.015)	(0.016)	(0.016)	(0.039)	(0.182)
Has fridge (0/1)	0.160***	0.160***	0.181***	0.181***	0.101***	-0.081
	(0.011)	(0.011)	(0.012)	(0.012)	(0.028)	(0.148)
Has kitchen (0/1)	0.091***	0.092***	0.082***	0.082***	0.185***	0.290

	(1)	(2)	(3)	(4)	(5)	(6)
	(0.014)	(0.014)	(0.014)	(0.014)	(0.043)	(0.207)
Owns computer (0/1)	0.078***	0.078***	0.107***	0.107***	-0.002	-0.378
	(0.015)	(0.015)	(0.016)	(0.016)	(0.052)	(0.316)
Owns decoder (0/1)	0.102***	0.102***	0.118***	0.118***	0.083***	-0.005
	(0.010)	(0.010)	(0.012)	(0.012)	(0.020)	(0.082)
Owns car (0/1)	0.472***	0.472***	0.470***	0.470***	0.526***	0.223
	(0.018)	(0.018)	(0.019)	(0.019)	(0.047)	(0.229)
EA FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,829	56,817	23,220	23,220	33,609	33,597
R-squared	0.509	0.509	0.606	0.606	0.412	-2.306
AR F-stat (p-val)	0.191	0.191	0.364	0.364	0.0539	5.93e-08
KP Wald F-stat	61.24	92.51	31.51	50.13	5.041	4.632
LM-weak	30.32	44.45	11.87	14.63	3.921	3.920

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01..

D.1.4. Internet connectivity and diversity of food products consumed, 2SLS estimates.

Dep var: # consumed commodities	(1)	(2)	(3)	(4)	(5)	(6)
			Urban		Rural	
Distance 2G+ (ln, km) x Internet	-0.339		-0.009		-2.407	
	(0.428)		(0.756)		(1.553)	
Distance 2G+ <2km (0/1) x Internet		0.861		0.024		4.993*
		(1.088)		(2.013)		(2.759)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56 829	56 817	23 220	23 220	33 609	33 597
Anderson-Rub. F-test (p-val.)	0.427	0.426	0.991	0.991	0.0385	0.0384
KP Wald F-stat	61.38	92.62	31.53	50.10	5.057	13.16
KP rank LM-stat	30.34	44.46	11.86	14.61	3.931	9.600

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01.

D.1.5. Internet connectivity and diversity of self-consumed food products, 2SLS estimates.

Dep var: # self-consumed commodities	(1)	(2)	(3)	(4)	(5)	(6)
			Urban		Rural	
Distance 2G+ (ln, km) x Internet	-0.147		-0.113		-2.177	
	(0.233)		(0.257)		(1.501)	
Distance 2G+ <2km (0/1) x Internet		0.374		0.301		4.514*
		(0.584)		(0.689)		(2.737)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56 829	56 817	23 220	23 220	33 609	33 597
Anderson-Rub. F-test (p-val.)	0.512	0.512	0.659	0.659	0.0649	0.0646
KP Wald F-stat	61.31	92.61	31.52	50.11	5.040	13.15
KP rank LM-stat	30.33	44.46	11.87	14.63	3.920	9.587

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01.

D.1.6. Internet connectivity and quantity of commodities consumed per HH member, 2SLS estimates.

Dep. Var.: quantities consumed / HH member (grams, ln)	(1)	(2)	(3)	(4)	(5)	(6)
			Urban		Rural	
Distance 2G+ (ln, km) x Internet	-0.038*		-0.031		-0.096*	
	(0.022)		(0.032)		(0.057)	
Distance 2G+ <2km (0/1) x Internet		0.094*		0.078		0.215*
		(0.055)		(0.080)		(0.125)
Observations	951 037	950 878	481 114	481 114	469 923	469 764
Anderson-Rub. F-test (p-val.)	0.0276	0.0277	0.117	0.117	0.0775	0.0779
KP Wald F-stat	265	385.4	160.6	291.2	46.56	89.77
KP rank LM-stat	156.5	193.2	83.47	81.24	34.75	60.91
Dep. Var.: quantities self-consumed / HH member (grams, ln)	(7)	(8)	(9)	(10)	(11)	(12)
			Urban		Rural	
Distance 2G+ (ln, km) x Internet	-0.055**		-0.071**		-0.036	
	(0.027)		(0.033)		(0.079)	
Distance 2G+ <2km (0/1) x Internet		0.137**		0.182**		0.079
		(0.067)		(0.085)		(0.168)
Observations	950,617	950,458	480,658	480,658	469,533	469,374
Anderson-Rub. F-test (p-val.)	0.0840	0.0843	0.334	0.334	0.0755	0.0758
KP Wald F-stat	265.7	386.7	160.9	292.4	46.85	91
KP rank LM-stat	157	193.9	83.87	81.34	34.89	61.47
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Commodity FEs	Yes	Yes	Yes	Yes	Yes	Yes
Conversion factor FEs	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in brackets, robust to heteroskedasticity and clustered by HH. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.1.7. Internet connectivity and quantity of commodities purchased per HH member, 2SLS estimates.

Dep. Var.: quantities of purchased commodity / HH member (grams, ln)	(1)	(2)	(3)	(4)	(5)	(6)
			Urban		Rural	
Distance 2G+ (ln, km) x Internet	-0.037		-0.010		-0.123**	
	(0.024)		(0.034)		(0.059)	
Distance 2G+ <2km (0/1) x Internet		0.093		0.025		0.283**
		(0.059)		(0.085)		(0.134)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Product-unit FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	757,895	757,790	415,375	415,375	342,126	342,021
Anderson-Rub. F-test (p-va.l)	0.116	0.116	0.770	0.770	0.0306	0.0305
KP Wald F-stat	272.2	373.4	159.7	283.1	54.58	92.98
KP rank LM-stat	165	195.2	85.54	79.16	39.74	64.22

Standard errors in brackets, robust to heteroskedasticity and clustered by HH. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.2. Mobile money channel.

D.2.1. Financial inclusion in the WAEMU

Variable	Obs	Mean	Std. Dev.	Min	Max
Standard bank account owner (0/1)	58,683	0.1528211	0.359818	0	1
Postal bank account owner (0/1)	58,683	0.0158308	0.1248218	0	1
Microfi account owner (0/1)	58,683	0.0883561	0.2838145	0	1
MM account owner (0/1)	58,683	0.3426887	0.4746125	0	1
Prepaid card owner (0/1)	58,683	0.0124568	0.1109135	0	1

D.2.2. Financial inclusion and HH expenditures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dep. var:	**Total expenditures (XOF, ln)**					**Food exp. (XOF, ln)**		**Non-food exp. (XOF, ln)**		**Food exp. (XOF, ln)**	
										Urban	Rural
Distance 2G+ <2km (0/1) x nb.tel	0.156***	0.177***	0.178***		0.138***		0.097***		0.054*	0.095**	0.318**
	(0.034)	(0.036)	(0.035)		(0.032)		(0.029)		(0.029)	(0.048)	(0.144)
Distance 2G+ <2km (0/1) x MM				0.203***	0.151**	0.212***	0.174**	0.007	-0.014	0.063	0.320*
				(0.068)	(0.065)	(0.067)	(0.068)	(0.069)	(0.070)	(0.105)	(0.185)
MM account owner (0/1)	-0.104***			-0.220***	-0.190***	-0.174***	-0.151***	-0.062	-0.049	-0.099	-0.166***
	(0.009)			(0.039)	(0.037)	(0.039)	(0.039)	(0.040)	(0.040)	(0.093)	(0.064)
Bank account owner (0/1)		0.030***									
		(0.011)									
Microfi account owner (0/1)			-0.008								
			(0.010)								
Internet	0.074***	0.081***	0.075***	0.087***	0.078***	0.006	-0.001	0.095***	0.092***	-0.078*	-0.099**
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.045)	(0.049)
Nb. tel	-0.066***	-0.050**	-0.067***	0.053***	-0.039*	0.011***	-0.054***	0.053***	0.017	0.012	-0.033
	(0.023)	(0.022)	(0.023)	(0.003)	(0.021)	(0.003)	(0.019)	(0.002)	(0.019)	(0.011)	(0.024)
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,188	56,188	56,188	56,188	56,188	56,188	56,188	56,188	56,188	22,988	33,200
AR F-stat	1.28e-07	1.27e-06	1.00e-07	0.00275	4.90e-06	0.00103	1.89e-05	0.918	0.172	0.127	9.06e-05
KP Wald F-stat	99.36	99.44	98.96	108.9	48.99	108.8	50.02	109.2	49.61	24.52	5.461
LM-weak	65.24	65.23	64.91	69.49	64.46	69.61	66.16	69.65	65.61	21.58	8.814

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Baseline HH controls included but not reported

D.2.3. Mobile money and food diversity

Dep var: # commodities	(1)	(2)	(3)	(4)	(5)	(6)
	Consumed commodities			Self-consumed commodities		
	All	Urban	Rural	All	Urban	Rural
Distance 2G+ <2km (0/1) x MM	0.523	-0.187	2.021	-0.408	-0.609	-1.254
	(0.951)	(1.585)	(2.302)	(0.471)	(0.588)	(1.258)
MM account owner (0/1)	1.715***	2.423*	0.687	0.407	0.670	0.750
	(0.548)	(1.388)	(0.824)	(0.280)	(0.530)	(0.461)
Internet	0.753***	0.732***	0.755***	-0.073*	-0.007	-0.084
	(0.141)	(0.205)	(0.182)	(0.043)	(0.041)	(0.078)
Nb. tel	0.608***	0.616***	0.487***	0.029**	0.004	0.094***
	(0.043)	(0.071)	(0.050)	(0.013)	(0.017)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,188	22,988	33,200	56,188	22,988	33,200
Anderson-Rub. F-test (p-val.)	0.583	0.906	0.387	0.392	0.292	0.320
KP Wald F-stat	108.9	71.34	20.79	108.9	71.34	20.79
KP rank LM-stat	69.49	19.74	16.06	69.49	19.74	16.06

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.2.4. Mobile money and quantity of commodities consumed per HH member, 2SLS estimates

Dep. Var.: quantities consumed / HH member (grams, ln)	(1)	(2)	(3)	(4)	(5)	(6)
	Consumed commodities			Self-consumed commodities		
	All	Urban	Rural	All	Urban	Rural
Distance 2G+ <2km (0/1) x MM	0.184***	0.148***	0.425***	-0.053	-0.014	-0.227*
	(0.038)	(0.057)	(0.090)	(0.053)	(0.078)	(0.134)
MM account owner (0/1)	-0.258***	-0.272***	-0.316***	0.026	0.005	0.087
	(0.026)	(0.051)	(0.040)	(0.035)	(0.071)	(0.056)
Internet	-0.029***	-0.049***	-0.006	-0.022***	-0.014***	-0.029***
	(0.006)	(0.007)	(0.009)	(0.005)	(0.004)	(0.010)
Nb. tel	0.016***	0.012***	0.025***	0.002	0.001	0.008***
	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	939,658	476,138	463,091	1,139,731	549,985	589,209
Anderson-Rub. F-test (p-val.)	1.57e-06	0.0101	1.25e-06	0.320	0.853	0.0891
KP Wald F-stat	673.9	311.5	195.5	824.3	377.4	184.3
KP rank LM-stat	515.6	145.8	154	518.2	149.1	132.7

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.2.5. Mobile money and quantity of commodities purchased per HH member, 2SLS estimates

Dep. Var.: quantities purchased / HH member (grams, ln)	(1)	(2)	(3)
	All	Urban	Rural
Distance 2G+ <2km (0/1) x MM	0.151***	0.103	0.438***
	(0.042)	(0.067)	(0.093)
MM account owner (0/1)	-0.276***	-0.275***	-0.367***
	(0.030)	(0.060)	(0.045)
Internet	-0.025***	-0.042***	-0.007
	(0.006)	(0.008)	(0.009)
Nb. tel	0.010***	0.010***	0.019***
	(0.002)	(0.003)	(0.003)
Controls	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes
Observations	749,176	411,346	337,437
Anderson-Rub. F-test (p-val.)	0.000479	0.127	4.50e-06
KP Wald F-stat	621.3	287.2	186.8
KP rank LM-stat	513.2	128.7	158

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.3. On-farm, off-farm activities and non-agricultural entrepreneurship

D.3.1. Mobile connectivity and income diversification, 2SLS estimates.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	**Share of HH members earning off-farm income**			**Share of HH members earning on-farm income**		
	All	Urban	Rural	All	Urban	Rural
Dist. 2G+ <2km (0/1) x # mob.	0.089***	0.081***	0.271***	0.056***	0.026	0.169**
	(0.019)	(0.030)	(0.105)	(0.015)	(0.027)	(0.068)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Product-unit FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,814	23,217	33,597	56,814	23,217	33,597
AR. F-test (p-val.)	5.10e-07	0.00484	5.02e-06	0.00024	0.363	0.00055
KP Wald F-stat	99.65	47.46	11.54	99.65	47.46	11.54
KP rank LM-stat	65.47	21.16	9.357	65.47	21.16	9.357

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.3.2. Mobile connectivity and entrepreneurship, 2SLS estimates.

	(1)	(2)	(3)
Dep. Var.:	**# of non-agricultural enterprises in the HH**		
	All	Urban	Rural

Dist. 2G+ <2km (0/1) x # mob.	0.113**	0.096	0.266*
	(0.045)	(0.111)	(0.148)
Time since first enterprise (years)	0.027***	0.018***	0.032***
	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes
Product-unit FEs	Yes	Yes	Yes
Observations	56,814	23,217	33,597
Anderson-Rub. F-test (p-val.)	5.10e-07	0.00484	5.02e-06
KP Wald F-stat	99.65	47.46	11.54
KP rank LM-stat	65.47	21.16	9.357

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E. E. Robustness checks

E.1. Estimations with converted food prices.

E.1.1. Network connectivity and food price levels

Dep. var.: $P_{z,j}$ (XOF/gram)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2nd-stage estimates											
	Product-unit prices						**Averaged product prices**					
	Price record 1			**Price record 2**			**Price record 1**			**Price record 2**		
Distance 2G+ (ln, km)	-0.060*			-0.059*			-0.085**			-0.085**		
	(0.034)			(0.034)			(0.038)			(0.037)		
Distance 2G+ <2km (0/1)		0.175*			0.171*			0.253**			0.251**	
		(0.098)			(0.099)			(0.113)			(0.112)	
Distance 2G+ <5km (0/1)			0.175*			0.171*			0.248**			0.247**
			(0.097)			(0.098)			(0.109)			(0.107)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-unit FE	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No
Product FE	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	356,603	356,494	356,468	356,605	356,496	356,470	184,057	183,990	183,973	184,055	183,988	183,971
AR F-test (p-val)	0.0658	0.0654	0.0647	0.0744	0.0740	0.0732	0.0176	0.0177	0.0170	0.0169	0.0170	0.0162
KP Wald F-stat	71.12	56.79	61.64	71.12	56.79	61.63	68.71	50.34	61.79	68.71	50.34	61.79
KP rank LM-stat	40.79	27.20	23.72	40.79	27.20	23.71	41.53	28.41	25.46	41.53	28.41	25.47

Standard errors in brackets, robust to heteroscedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

E.1.2. Network connectivity and food price convergence, urban versus rural areas.

Var. dép.: $P_{z,j}$ (XOF/gram)	(1)	(2)	(3)	(4)	(5)	(6)
	2nd-stage estimates					
	Price record 1			**Price record 2**		
Distance 2G+ (ln, km)	-0.109**			-0.111**		
	(0.050)			(0.050)		
Distance 2G+ x urbain (0/1)	0.140*			0.140*		
	(0.083)			(0.082)		
Distance 2G+ <2km (0/1)		0.268*			0.334**	
		(0.140)			(0.148)	
Distance 2G+ <2km x urbain (0/1)		-0.363*			-0.382*	
		(0.201)			(0.217)	
Distance 2G+ <5km (0/1)			0.316**			0.321**
			(0.143)			(0.142)
Distance 2G+ <5km x urbain (0/1)			-0.413			-0.414*
			(0.253)			(0.249)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Product-unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	356,605	353,495	356,470	356,603	356,494	356,468
AR F-test (p-val)	0.0783	0.112	0.0730	0.0701	0.0698	0.0652
KP Wald F-stat	31.21	27.54	31	31.21	27.82	31
KP rank LM-stat	46.08	37.09	28.09	46.08	36.19	28.09

Standard errors in brackets, robust to heteroscedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

E.1.3. Network connectivity and food price dispersion.

Var. dép.: $CV_{d,j(,u)}$	(1)	(2)	(3)	(4)
	2^{nd}-stage estimates			
	Price record 1	**Price record 2**	**Price record 1**	**Price record 2**
2G+ coverage (% dpt)	-0.456	-0.510*	-0.491*	-0.540*
	(0.283)	(0.283)	(0.278)	(0.278)
Price level (XOF/gram)			0.008**	0.007*
			(0.004)	(0.004)
Average $CV_{d,j(,u)}$	0,220	0.220	0.220	0.220
Controls	Yes	Yes	Yes	Yes
Region-product FE	Yes	Yes	Yes	Yes
Observations	24,535	24,535	24,535	24,535
Anderson-Rub. F-test (p-val)	0.0955	0.0598	0.0654	0.0414
KP Wald F-stat	35.38	35.38	35.31	35.32
KP rank LM-stat	35.33	35.33	35.27	35.28

Standard errors in brackets, robust to heteroscedasticity and clustered by region-product. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Reported first-stage statistics robust to heteroskedasticity and clustering.

E.1.4. Network connectivity and the demand channel

Var. dép.: $P_{z,j}$ (XOF/gram)	(1)	(2)	(3)	(4)
	2^{nd}-stage estimates			
	Price record 1	Price record 2	Price record 1	Price record 2
Distance 2G+ <2km (0/1)	-0.963	-1.108*	-1.666*	-1.813*
	(0.656)	(0.647)	(0.970)	(0.965)
Distance 2G+ <2km x EA food spending	0.056*	0.064*	0.095**	0.102**
	(0.033)	(0.033)	(0.048)	(0.048)
EA food spending (XOF, ln)	0.096	0.085	0.111*	0.142*
	(0.063)	(0.060)	(0.065)	(0.081)
EA non-food spending (XOF, ln)	-0.133*	-0.124*	-0.144**	-0.167**
	(0.068)	(0.065)	(0.073)	(0.083)
Controls	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Product-unit FE	Yes	Yes	No	No
Product FE	No	No	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Observations	356,496	356,494	183,990	183,988
AR F-test (p-val)	0.0855	0.0588	0.0130	0.00979
KP Wald F-stat	29.09	29.09	25.93	25.93
KP rank LM-stat	26.74	26.74	27.98	27.98

Standard errors in brackets, robust to heteroscedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

E.2. Augmented network coverage variable

E.2.1. Network connectivity and non-converted food product price

Var. Dep: non converted price (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Second-stage estimates							
	Price record 1				**Price record 2**			
1 well-captured network (0/1) x Distance 2G+ <2km (0/1)	0.119***				0.126***			
	(0.037)				(0.036)			
2 well-captured networks (0/1) x Distance 2G+ <2km (0/1)		0.135***				0.143***		
		(0.042)				(0.042)		
3 well-captured networks (0/1) x Distance 2G+ <2km (0/1)			0.157***				0.165***	
			(0.048)				(0.048)	
# well-captured networks x Distance 2G+ <2km (0/1)				0.045***				0.048***
				(0.014)				(0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-product-unit FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,670	129,670	129,670	129,670	129,668	129,668	129,668	129,668
AR F-stat	0.000606	0.000606	0.000606	0.000606	0.00473	0.000215	0.000215	0.000215
KP Wald F-stat	43.87	35.76	31.97	39.78	39.12	35.76	31.97	39.78
LM-weak	30.25	23.97	21.67	26.28	26.99	23.97	21.67	26.28

Standard errors in brackets, robust to heteroscedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

D.4.2. Network connectivity and converted food product price

Var. Dep: converted price (XOF/gram)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Second-stage estimates							
	Price record 1				Price record 2			
1 well-captured network (0/1) x Distance 2G+ <2km (0/1)	0.189*				0.193*			
	(0.111)				(0.111)			
2 well-captured networks (0/1) x Distance 2G+ <2km (0/1)		0.212*				0.217*		
		(0.124)				(0.124)		
3 well-captured networks (0/1) x Distance 2G+ <2km (0/1)			0.238*				0.244*	
			(0.140)				(0.140)	
# well-captured networks x Distance 2G+ <2km (0/1)				0.071*				0.073*
				(0.042)				(0.041)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-product FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	353,736	353,736	353,736	353,736	353,734	353,734	353,734	353,734
AR F-stat	0.0855	0.0855	0.0855	0.0855	0.0770	0.0770	0.0770	0.0770
KP Wald F-stat	52.50	42.93	36.57	45.44	52.50	42.93	36.57	45.44
LM-weak	27.99	22.32	19.93	23.81	27.99	22.32	19.93	23.81

Standard errors in brackets, robust to heteroscedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01. Reported first-stage statistics robust to heteroskedasticity and clustering.

D.4.3. Network connectivity and non-converted food price convergence, urban versus rural areas.

Var. Dep: non converted price (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2nd-stage estimates							
	Price record 1				Price record 2			
(A) 1 well-captured network x Distance 2G+ <2km (0/1)	0.162***				0.164***			
	(0.041)				(0.040)			
(A) x urban (0/1)	-0.130**				-0.116**			
	(0.052)				(0.053)			
(B) 2 well-captured networks x Distance 2G+ <2km (0/1)		0.201***				0.202***		
		(0.052)				(0.050)		
(B) x urban (0/1)		-0.169***				-0.152**		
		(0.065)				(0.066)		
(C) 3 well-captured networks x Distance 2G+ <2km (0/1)			-0.857				-0.696	

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			(2.748)				(2.362)	
(C) x urban (0/1)			1.727				1.469	
			(4.564)				(3.923)	
(D) # well-captured networks x Distance 2G+ <2km (0/1)				0.074***				0.074***
				(0.019)				(0.018)
(D) x urban (0/1)				-0.069**				-0.062**
				(0.029)				(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-prod-unit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,670	129,670	129,670	129,670	129,668	129,668	129,668	129,668
AR F-test (p-val)	3.84e-05	3.84e-05	3.84e-05	3.84e-05	1.25e-05	1.25e-05	1.25e-05	1.25e-05
KP Wald F-stat	21.86	17.89	0.0815	9.637	21.86	17.89	0.0816	9.638
KP rank LM-stat	26.20	24.41	0.211	10.07	26.22	24.44	0.211	10.08

Standard errors in brackets, robust to heteroscedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

D.4.4. Network connectivity and converted food price convergence, urban versus rural areas.

Var. Dep: converted price (XOF per gram)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2nd-stage estimates							
	Price record 1				**Price record 2**			
(A) 1 well-captured network <2km (0/1)	0.334**				0.340**			
	(0.154)				(0.153)			
(A) x urban (0/1)	-0.356*				-0.360*			
	(0.214)				(0.212)			
(B) 2 well-captured networks <2km (0/1)		0.409**				0.417**		
		(0.188)				(0.187)		
(B) x urban (0/1)		-0.418*				-0.422*		
		(0.245)				(0.243)		
(C) 3 well-captured networks <2km (0/1)			1.263				1.278	
			(0.822)				(0.820)	
(C) x urban (0/1)			-1.703				-1.718	
			(1.367)				(1.366)	
(D) # well-captured networks <2km (0/1)				0.150**				0.153**
				(0.069)				(0.069)
(D) x urban (0/1)				-0.165*				-0.167*
				(0.099)				(0.098)

Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-prod-unit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	353,736	353,736	353,736	353,736	353,734	353,734	353,734	353,734
AR F-test (p-val)	0.0833	0.0833	0.0833	0.0833	0.0731	0.0731	0.0731	0.0731
KP Wald F-stat	25.57	21.43	2.029	22.46	25.58	21.43	2.028	22.46
KP rank LM-stat	32.42	26.57	3.193	28.39	32.42	26.58	3.193	28.40

Standard errors in brackets, robust to heteroscedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Reported first-stage statistics robust to heteroskedasticity and clustering.

D.4.5. Network connectivity and quantities of food product consumed

Dep var: quantities of consumed commodity / HH member (grams, ln)	(1)	(2)	(3)	(4)
	2nd stage estimates			
1 well-captured network (0/1) x Dist. 2G+ <2km (0/1) x # mob. cell	0.155***			
	(0.023)			
2 well-captured networks (0/1) x Dist. 2G+ <2km (0/1) x # mob. cell		0.167***		
		(0.025)		
3 well-captured networks (0/1) x Dist. 2G+ <2km (0/1) x # mob. cell			0.184***	
			(0.028)	
# well-captured networks x Dist. 2G+ <2km (0/1) x # mob. cell				0.053***
				(0.008)
Internet access (0/1)	-0.025***	-0.025***	-0.017**	-0.023***
	(0.007)	(0.007)	(0.007)	(0.007)
# mobile cell in the HH	-0.097***	-0.099***	-0.086***	-0.091***
	(0.017)	(0.018)	(0.015)	(0.016)
No. self-consumed commodities (O/1)	-0.004***	-0.004***	-0.005***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
HH size	-0.099***	-0.096***	-0.095***	-0.097***
	(0.005)	(0.005)	(0.005)	(0.005)
Nbr adults-equiv. FAO	0.030***	0.026***	0.026***	0.027***
	(0.006)	(0.007)	(0.007)	(0.007)
HHH gender	-0.034***	-0.035***	-0.037***	-0.035***
	(0.008)	(0.008)	(0.009)	(0.008)
HHH age	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
HHH literacy	0.007	0.008	0.004	0.006
	(0.007)	(0.007)	(0.008)	(0.007)
Married monogamous (O/1)	-0.143***	-0.144***	-0.140***	-0.142***
	(0.008)	(0.009)	(0.009)	(0.008)
Married polygamist (O/1)	-0.054***	-0.055***	-0.051***	-0.054***
	(0.011)	(0.011)	(0.011)	(0.011)
Banked (0/1)	0.348***	0.352***	0.363***	0.355***
	(0.014)	(0.014)	(0.015)	(0.014)
No education (O/1)	-0.022	-0.021	-0.014	-0.017
	(0.014)	(0.014)	(0.014)	(0.014)
Primary education (O/1)	-0.037***	-0.035***	-0.028**	-0.032**
	(0.013)	(0.013)	(0.014)	(0.013)
Secondary educ gen 1 (O/1)	-0.031**	-0.026**	-0.024*	-0.026**
	(0.013)	(0.013)	(0.014)	(0.013)
Secondary educ gen 2 (O/1)	-0.030**	-0.031**	-0.023	-0.027*
	(0.014)	(0.014)	(0.015)	(0.014)
Use electric grid (O/1)	0.024***	0.023**	0.031***	0.025***
	(0.009)	(0.009)	(0.010)	(0.009)
Uses solar elec/genset. (O/1)	0.034***	0.037***	0.043***	0.039***
	(0.008)	(0.009)	(0.009)	(0.008)
Healthy waste disposal (O/1)	0.006	0.004	0.005	0.005
	(0.008)	(0.008)	(0.008)	(0.008)
Healthy toilets (O/1)	0.038***	0.039***	0.037***	0.037***
	(0.008)	(0.008)	(0.009)	(0.008)
Healthy excrement disposal (O/1)	0.020***	0.022***	0.026***	0.021***
	(0.007)	(0.008)	(0.008)	(0.008)
Sanitary sewage disposal (O/1)	0.023**	0.024**	0.023**	0.025**
	(0.010)	(0.011)	(0.011)	(0.011)
Idiosyncratic demographic shock (O/1)	-0.015***	-0.016***	-0.014**	-0.015***
	(0.005)	(0.005)	(0.006)	(0.005)

Common natural shock (O/1)	-0.020***	-0.018***	-0.018***	-0.019***
	(0.006)	(0.006)	(0.006)	(0.006)
Common economic shock (O/1)	-0.022***	-0.022***	-0.021***	-0.022***
	(0.006)	(0.006)	(0.006)	(0.006)
Idiosyncratic economic shock (O/1)	-0.008	-0.008	-0.010	-0.009
	(0.007)	(0.007)	(0.008)	(0.007)
Common violence shock (O/1)	-0.026**	-0.030**	-0.031**	-0.029**
	(0.013)	(0.013)	(0.013)	(0.013)
Other shock (O/1)	-0.027	-0.024	-0.020	-0.023
	(0.017)	(0.017)	(0.018)	(0.017)
Rainfed/irrigated surface area ratio	-0.000*	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Indiv/collective plot surface area ratio	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Total area of plots	0.000**	0.000**	0.000*	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Tenant (0/1)	0.020**	0.023**	0.024**	0.021**
	(0.009)	(0.010)	(0.010)	(0.009)
Wall in final materials (0/1)	0.004	0.002	0.005	0.003
	(0.007)	(0.007)	(0.007)	(0.007)
Roof in final materials (0/1)	0.023**	0.025***	0.023**	0.021**
	(0.009)	(0.009)	(0.009)	(0.009)
Floor in final materials (0/1)	0.037***	0.039***	0.038***	0.036***
	(0.008)	(0.008)	(0.008)	(0.008)
TV (O/1)	-0.002	-0.001	0.006	0.001
	(0.008)	(0.008)	(0.008)	(0.008)
Iron (O/1)	-0.002	-0.003	0.008	0.001
	(0.015)	(0.015)	(0.016)	(0.015)
Fridge (O/1)	-0.004	-0.005	-0.008	-0.005
	(0.010)	(0.010)	(0.011)	(0.010)
Kitchen (O/1)	0.012	0.011	0.008	0.009
	(0.013)	(0.014)	(0.015)	(0.014)
Computer (O/1)	-0.032**	-0.033**	-0.039**	-0.035**
	(0.014)	(0.015)	(0.016)	(0.015)
Decoder (O/1)	0.014	0.013	0.012	0.014
	(0.009)	(0.010)	(0.010)	(0.009)
Owns car (O/1)	0.016	0.010	0.014	0.009
	(0.015)	(0.016)	(0.017)	(0.016)
EA FEs	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes
Commodity FEs	Yes	Yes	Yes	Yes
Conversion factor FEs	Yes	Yes	Yes	Yes
Observations	950,878	950,878	950,878	950,878
AR F-stat (p-value)	0	0	0	0
KP Wald F-stat	320.5	268.6	194	310.8
LM-weak	225.8	198.6	173.4	236.5

Standard errors in brackets, robust to heteroscedasticity and clustered by HH. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.3. Dealing with spatial anonymization

D.5.1. Alternative extraction methods

While a range of coordinate masking techniques exist, the technique that is currently used by the DHS and LSMS randomly offsets precise EA coordinates by zero to two kilometers (km) in urban areas and two to five km in rural areas, with one percent of rural areas displaced up to ten km (Blankespoor et al., 2021; Michler et al., 2022).

Based on Michler et al. (2022), we employ two alternative approaches to extract geolocated data. The first alternative method is a bilinear extraction, which involves calculating the distance-weighted average of the values of the four raster file cells closest to the centroid of each EA. The second method is a polygonal extraction, which involves calculating the weighted zonal average, i.e. the average of all cells covered by the polygon representing a buffer zone of 2 km around the centroid of an urban EA and 10 km around the centroid of a rural EA. Finally, to calculate the average annual number of lightning strikes at district level, we overlaid the raster layer with a shapefile containing the administrative district boundaries for the eight countries in the WAEMU LSMS survey. We then extracted the average annual number of lightning strikes within each administrative district.

D.5.2. First-stage estimation: OLS estimations of Eq. (3).

Dep var:	(1) Dist. network. (km)	(2) Dist. network. (ln, km)	(3) Dist < 5km (0/1)	(4) Dist < 2km (0/1)
		Panel A.		
Lightning risk – bilinear extraction	7631.3***	799.1***	-264.6***	-261.0***
	(2039.0)	(120.7)	(40.27)	(50.09)
Control var. (X_z)	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Observations (# EA)	4,646	4,646	4,644	4,645
R2	0.846	0.766	0.641	0.664
		Panel B.		
Lightning risk – polygonal extraction	9659.2***	1001.3***	-312.1***	-323.0***
	(2505.5)	(178.8)	(61.95)	(75.00)
Control var. (X_z)	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes
Observations (# EA)	4,305	4,305	4,303	4,304
R2	0.846	0.762	0.635	0.659

Standard errors in brackets, robust to heteroskedasticity and clustered by district. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.5.3. Price level and spatial convergence, 2SLS estimations of Eq. (4) and (5).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var (XOF, ln):	Record 1		Record 2		Record 1		Record 2	
	IV - bil	**IV -poly**	**IV - bil**	**IV -poly**	**IV - bil**	**IV -poly**	**IV - bil**	**IV -poly**
Distance 2G+ <2km (0/1)	0.110***	0.108***	0.117***	0.113***	0.150***	0.150***	0.153***	0.155***
	(0.035)	(0.033)	(0.035)	(0.033)	(0.039)	(0.036)	(0.038)	(0.035)
Distance 2G+ <2km (0/1) x urban					-0.119***	-0.133**	-0.106**	-0.129**
					(0.046)	(0.054)	(0.047)	(0.056)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-prod-unit FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	EA	EA	EA	EA	EA	EA	EA	EA
Observations	129,670	121,477	129,668	121,475	129,670	121,477	129,668	121,475
AR F-stat (p-val)	0.00081	0.00027	0.00026	0.00012	5.31e-05	4.0e-07	1.7e-05	9.0e-08
KP Wald F-stat	47.59	46.13	47.59	46.12	23.22	21.25	23.22	21.25
LM-weak	31.62	32.92	31.62	32.92	37.23	45.49	37.23	45.71

Standard errors in brackets, robust to heteroskedasticity and clustered by district. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.4. Reduced-form estimations

D.6.1. Price level and dispersion, 2SLS estimations of Eq. (4)-(6)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var:	Ln $P_{d,j,u}$(XOF, prod-unit)					CV Ln $P_{d,j,u}$
IV- Lightning		-29.634***	-27.492***	-35.607***	-33.360***	
		(8.785)	(9.239)	(9.003)	(9.413)	
IV- Lightning x urban				27.869**	28.153**	
				(12.137)	(12.171)	
IV- Unweighted lightning						0.0017***
						(0.0006)
2015 pop. density	-0.00000193*	-0.00000196*	-0.0000023**	-0.00000195*	-0.0000023**	-0.000
	(0.0000010)	(0.0000010)	(0.000001)	(0.0000010)	(0.000001)	(0.000)
2020 pop. density (ln)	-	-	0.0022	-	0.0024	
	-	-	(0.0028)	-	(0.0028)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
District-product-unit FEs	Yes	Yes	Yes	Yes	Yes	No
Region-prod-unit FEs	No	No	No	No	No	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	EA	EA	EA	EA	EA	Region-prod.
Observations	129,740	129,740	129,740	129,740	129,740	19,450
R^2	0.967	0.967	0.967	0.968	0.967	0.500

Standard errors in brackets, robust to heteroskedasticity and clustered at differing administrative levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Estimates with the first price record are reported.

D.6.2. HH demand for food products, 2SLS estimations of Eq. (7).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Spending / HH member		Diversity (#)		Quantities (g / HH member)		
Dep. Var:	Food	Non-food	Consumed	Self-cons.	Consumed	Self-cons.	Purchased
IV- Lightning risk x # nb. mobile	-50.313***	-25.193**	-740.15**	683.413***	-94.741***	39.522***	-143.660***
	(11.534)	(11.477)	(172.70)	(103.481)	(10.666)	(12.397)	(12.053)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product-unit FEs	-	-	-	-	Yes	Yes	Yes
Clustering	EA	EA	EA	EA	HH	HH	HH
Observations	56,829	56,829	56,829	56,829	950,617	1,153,952	757,895
R^2	0.705	0.705	0.622	0.631	0.758	0.393	0.815

Standard errors in brackets, robust to heteroskedasticity and clustered at differing administrative levels. * p < 0.1, ** p < 0.05, *** p < 0.01.

E.5. Testing the exclusion restriction

D.7.1. Controlling for average daily rainfall precipitations

Dep. Var: Ln $P_{d,j,u}$ (XOF, prod-unit)	(1) 2nd stage	(2) 1st stage	(3) 2nd stage	(4) 1st stage	(5) 2nd stage	(6) 1st stage	(7) 2nd stage	(8) 1st stage
Dist. 2G+ <2km (0/1)	0.110***		0.106***		0.112***		0.113***	
	(0.034)		(0.036)		(0.036)		(0.036)	
IV- Lightning risk		-266.62***		-265.22***		-267.02***		-267.07***
		(38.714)		(38.582)		(38.465)		(38.494)
Rainfall 2018-19	-0.014**	0.004					-0.032***	-0.006
	(0.007)	(0.023)					(0.008)	(0.025)
Rainfall 2017			0.025**	0.026				
			(0.010)	(0.036)				
Av. rainfall 2015-19					0.022*	0.025	0.052***	0.031
					(0.012)	(0.046)	(0.015)	(0.052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District-prod-unit FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,670	129,670	129,670	129,670	129,670	129,670	129,670	129,670
AR F-stat (pval)	0.0008		0.00152		0.0008		0.0008	
KP Wald F-stat	47.43		47.25		48.19		48.14	
LM-weak	31.73		32.11		31.83		31.82	

Standard errors in brackets, robust to heteroskedasticity and clustered at the EA level. * p < 0.1, ** p < 0.05, *** p < 0.01. Rainfall precipitation data drawn from the MSWEP V2.8 database (Beck et al., 2019).

D.7.2. Lightning strikes, connectivity and EA-level expenditures, OLS estimations.

Dep. Var: EA spend. (XOF, ln)	(1) **Total**	(2) **Food**	(3) **Non-food**	(4) **Total**	(5) **Food**	(6) **Non-food**
IV- Lightning risk	-302.445**	-276.731**	-328.789**	41.328	40.011	48.178
	(128.911)	(126.545)	(133.748)	(132.182)	(128.604)	(138.409)
Pop. Density, 2015	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dist. 2G+ (km, ln)				**-0.281*** **	**-0.258*** **	**-0.308*** **
				(0.023)	**(0.022)**	**(0.023)**
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,643	4,643	4,643	4,643	4,643	4,643
R-squared	0.443	0.414	0.475	0.472	0.440	0.506

Standard errors in brackets, robust to heteroskedasticity and clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

D.7.3. Lightning strikes, connectivity and EA-level farm sales, OLS estimations.

Dep. Var: EA farm sales. (XOF, ln)	(1)	(2)	(3)
IV- Lightning risk	405.320	469.593*	-256.904
	(285.373)	(261.924)	(251.501)
Pop. Density, 2015	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)
EA total spend. (XOF, ln)		0.310***	0.688***
		(0.092)	(0.095)
Dist. 2G+ (km, ln)			**0.446*** **
			(0.090)
District FEs	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes
Observations	3,708	3,708	3,708
R-squared	0.395	0.398	0.411

Standard errors in brackets, robust to heteroskedasticity and clustered at the district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

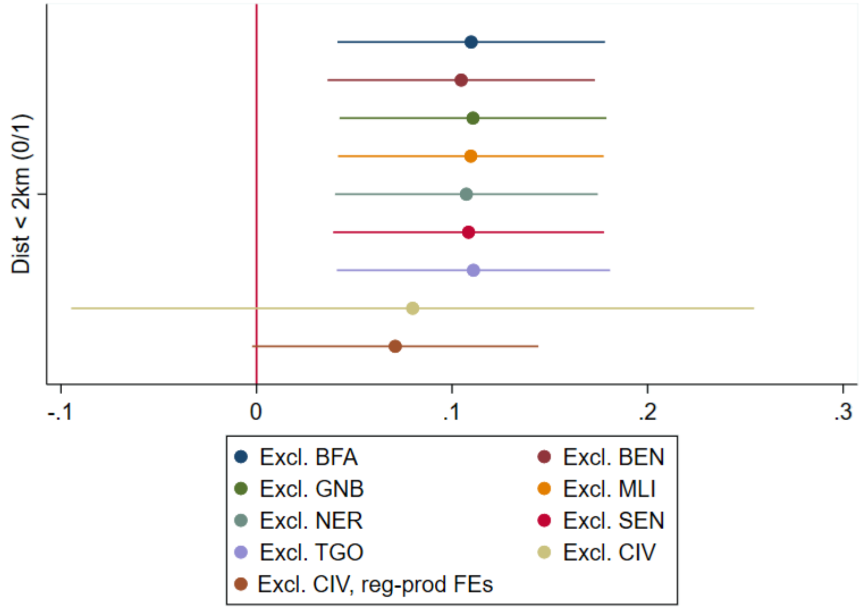
E.6. Additional tests

E.6.1. Digital spillovers and SUTVA violation, 2SLS estimations.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var (ln) :	**HH food spend pc (XOF)**			**HH food-prod consumption pc (grams)**		
(A) Distance 2G+ <2km (0/1) x # mob. cell	0.127***	0.153***	0.140***	0.196***	0.228***	0.233***
	(0.030)	(0.039)	(0.045)	(0.032)	(0.043)	(0.054)
(B) Distance 2G+ <2km (0/1)			-0.302*			-0.347**
			(0.180)			(0.137)
Spillovers controls:						
(C) Mobile incidence x # mob. cell		-0.236***	-0.181**		-0.353***	-0.304***
		(0.076)	(0.078)		(0.090)	(0.094)
(D) Mobile incidence			0.271***			0.372***
			(0.099)			(0.121)
(E) # mob. cell	-0.076***	0.131***	0.088*	-0.076***	0.131***	0.132**
	(0.020)	(0.050)	(0.048)	(0.020)	(0.050)	(0.055)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	No	Yes	Yes	No
District FEs	No	No	Yes	No	No	Yes
Prod-unit FEs	No	No	No	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,817	56,817	55,466	950,458	950,458	923,548
AR F-stat (p-val)	1.29e-05	2.32e-05	0.00168	1.15e-08	2.03e-08	1.15e-06
KP Wald F-stat	102.3	74.82	13.24	99.05	80.22	6.991
LM-weak	67.66	44.51	9.420	66	44.34	5.227

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E.6.2. Testing the sensitivity to individual country's exclusion



Note: 2SLS estimations of Equation (4), excluding countries one by one.

“ Sur quoi la fondera-t-il l’économie du monde qu’il veut gouverner ? Sera-ce sur le caprice de chaque particulier ? Quelle confusion ! Sera-ce sur la justice ? Il l’ignore. ”

Pascal

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