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 markets and rural livelihoods in the WAEMU. Using survey data covering 59,319 households and 146 food products traded in 4,983 enumeration areas, instrumental variable estimations support that connectivity reduces food price dispersion by fostering a catch-up effect in rural areas. Importantly, this analysis highlights the role of demand-side mechanisms in explaining price patterns. Results show that mobile connectivity not only increases food product consumption, but it also reduces self-consumption among connected rural households. Mobile money adoption and access to off-farm revenues are identified as enablers of increased food demand.

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

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INTRODUCTION

The persistence of low agricultural productivity and pervasiveness of 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; Suri & Udry, 2022; Huneeus & Rogerson, 2023). Reducing information search, distance, and other transaction costs is therefore a major challenge for African agri-food systems and rural households alike, often plagued with missing or remote infrastructures, harsh climatic conditions, and underdeveloped financial markets (Aker & Mbiti, 2010; Aker & Cariolle, 2023). Widespread access to mobile technologies in the region has significantly reduced those costs, with a mixed impact on agricultural productivity but clear benefits on agricultural market functioning (Aker & Mbiti, 2010; Suri & Udry, 2022; Aker & Cariolle, 2023). Mobile connectivity has indeed been found to spur food price convergence through improved spatial allocation of agricultural supplies and stronger bargaining power of better-informed farmers. Yet, little attention has been paid to the demand-side effects of mobile phone access on agri-food systems, whereas mobile diffusion has also stimulated food consumption by improving access to income sources off the farm and to mobile money services (Jack & Suri, 2014; Suri et al., 2023; Masaki et al., 2020; Bahia et al., 2021, 2024).

The objective of this paper is to fill this gap by linking the impact of mobile connectivity on food market prices to household demand for food products in the West African Economic and Monetary Union (WAEMU). Our analysis distinctly highlights the role of rural households' food consumption in explaining price patterns, considering a broad range of food products. We also show evidence on two particular mechanisms through which household demand for food products may have increased: financial inclusion through mobile money, and income diversification through off-farm and non-agricultural activities. Finally, we provide evidence of a negative externality of mobile connectivity on households without access to mobile phones, who find themselves faced with a rising cost of living without benefiting from the digitalization process.

To do this, we use survey data covering 59,319 households and 146 food products traded in 4,983 enumeration areas in the region, and show over a regional scale that mobile connectivity reduces food price dispersion by spurring food prices catch-up in rural areas. Our empirical approach relies on an instrumental variable (IV) setup, popularized in the political economy literature by Guriev et al (2021) and Manacorda and Tesei (2020), which consists in instrumenting the mobile-internet network coverage in a location by its past exposure to lightning strikes.[1]

Our findings provide an original and coherent picture of rural transformations induced by mobile connectivity across the region. Firstly, estimations show that areas covered by the mobile network observe 10 to 12%-higher food product prices compared to EAs located further away from the network, and this effect is driven by a food-price catchup in rural areas. At the district level, the analysis shows that a 10% increase in network coverage leads to a 5% drop in the coefficient of variation of food prices. These numbers are consistent with findings of individual empirical

[1] 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. Multiple robustness checks to ensure the validity of the instrument are conducted, paying a particular attention to possible violation of the exclusion restriction assumption.

studies conducted on distinct specific commodities at the national or local levels throughout the region.[2]

Secondly, our analysis reveals that food demand fully explains observed price patterns. Estimations show that when a household acquires a mobile phone in an area covered by the mobile network, it significantly increases total spending (+13%), especially in rural areas (+37%). These effects on consumption spending are close in magnitude to estimates provided by similar studies conducted in West African countries (Masaki et al., 2020; Bahia et al, 2024). Mobile connectivity is also found to increase both consumed and purchased food quantities, while reducing household reliance on self-consumption. Quantities consumed and purchased by connected households indeed increase by 20% and 29%, respectively, while self-consumed quantities fall by 9%. Again, this effect of connectivity is particularly pronounced for rural households, who experienced a 41% and 61% increase in consumed and purchased quantities of food products, respectively, and a 19% drop in self-consumed quantities. Additionally, we find that mobile network proximity reduces food expenditures in non-connected households by 28%, suggesting the presence of a negative externality that is likely related to rising food prices.

Lastly, our analysis reveals that financial inclusion through mobile money adoption, and income diversification through increased off-farm activities and non-agricultural entrepreneurship, have supported the demand for food products in rural communities. Estimations show that mobile money account ownership increases household food expenditures by 17%, more markedly in rural areas (+32%), with no significant effects observed in urban areas. Similar spatial demand patterns are evidenced when focusing on the quantities of products consumed and purchased by household members. Regarding off-farm and nonagricultural revenues, estimations show that mobile connectivity respectively increases the share of household members earning off-farm and on-farm incomes by 9% and 6%, respectively, stressing that connectivity increases the relative share of household members engaged in off-farm revenue-generating activities. In the same way, mobile connectivity significantly increases the number of nonagricultural enterprises within the household. These effects are stronger for rural households, and are in line with recent empirical evidence on increased labor force participation, wage employment, and non-farm/off-farm self-employment in Tanzania and Nigeria (Bahia et al., 2021, 2024).

This paper makes several contributions to the literature. First and foremost, it contrasts to a substantial literature that has emphasized the role of supply-driven mechanisms, such as improved spatial allocation of agricultural supplies or stronger bargaining power induced by better-informed farmers and traders, 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). This paper is the first to highlight how rural transformations induced by mobile connectivity have shaped households' demand for food products and influenced food price convergence patterns. Second, our analysis also confirms the external validity of results provided

[2] For instance, studies conducted in Ghana, have found that access to market information through ICTs increases maize prices by 10%, groundnut prices by 7% (Courtois & Subervie, 2015), and yam prices by 9% (Soldani et al., 2023). In Niger, Aker (2010) shows that mobile coverage reduces by 10 to 16% trader price dispersion across grain markets, while Aker and Fafchamps (2015) find that it reduced the spatial dispersion of producer prices for cowpea by 6 percent. A literature review is provided in Online appendix F.

by interdependent bodies of the digital-for-development literature over a large multi-country scale, namely those related to commodity price levels and price dispersion (Jensen, 2007; Aker, 2010; Goyal, 2010; Soldani et al., 2021), food consumption (Masaki et al., 2020; Bahia et al., 2021, 2024), and labor force participation (Bahia et al., 2024). Third, it introduces a methodological innovation by employing conversion factors for non-standard measurement units, enabling us to assess consumed quantities and prices per gram for a broad spectrum of 146 food products traded across the WAEMU zone.

Taken together, our analysis supports that West African economies and rural HHs may be subject to profound economic transformations, prompted by the digital interconnection process in rural areas. This evidence on the demand-side effects of mobile technologies has critical policy implications, especially in West Africa where rural economies are heavily reliant on the often stagnant rainfed agricultural sector, highly vulnerable to climatic and geopolitical risks, and where the rural labor force is progressively shifting away from agriculture to the service sector (Suri & Udry, 2022). As a result, digitalization policies that go beyond strict support to farming and also address failures in complementary markets such as the financial or the labor markets, may not only have a profound impact on the agricultural sector, but trigger or accelerate deep transformations in rural livelihoods. However, an important side effect of mobile connectivity is the negative externality on households with no or limited access to mobile phones. These households do not benefit from the digital dividends of mobile technology, while they find themselves faced with rising food costs. 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. In Section I, we lay out the background on mobile connectivity and rural livelihoods in West Africa. In Section II, we present the data and the empirical strategy. Section III presents and discusses our main results. In Section IV, we analyze how mobile connectivity may affect HH demand for food products. Section V presents the robustness analysis. Section VI concludes.

I. BACKGROUND

A. Food Markets in the WAEMU

Food markets in the WAEMU are characterized by significant diversity and variability and are influenced by factors such as precipitation and climate, soil type, population density, and available infrastructure. With a combined population of approximately 137 million, the WAEMU region had a collective nominal GDP of 178 billion US dollars in 2022 with a GDP per capita of 1,243 US dollars (IMF, 2024). In 2022, the percent of the population employed in agriculture ranged from a low of 22% in Senegal to a high of 74% in Burkina Faso, with a percent rural population ranging from 47% in Côte d'Ivoire to 83% in Niger (World Bank, 2024). The majority of rural residents in the region are smallholder farmers who depend on rainfed cultivation.

Throughout the WAEMU region, significant price dispersion exists within and across regions for major food commodities in the WAEMU zone, mainly due to high search and transaction costs as grain traders often face long distances between markets and poor-quality roads when seeking price information (Aker, 2010; Aker & Fafchamps, 2015).

B. Mobile connectivity in the WAEMU

Although the first mobile phones were introduced to the region in the late 1990s, the WAEMU zone has experienced significant advances in rollout of mobile connectivity and geographic coverage over the last decade. Beginning in the early 2000s, mobile penetration rates have surged for countries in the region, with over 100 mobile subscriptions per 100 residents in all countries but Niger (56 per 100) and Togo (74 per 100) in 2022.[3] In terms of coverage, WAEMU member states had more than 90% of their population covered by the mobile cellular network in 2021 (World Bank, 2024).

Despite the impressive advances in mobile phone penetration across the region, there nevertheless exists a digital divide between well-connected urban areas and less well-connected rural areas. Aside from facing lower connectivity in rural areas, many rural households are unable to afford the cost of purchasing a mobile phone and airtime credit (Granguillhome Ochoa et al., 2022). Additionally, mobile broadband internet coverage is lower than simple access to a mobile feature phone, with only 20% of WAEMU households reporting using mobile broadband in 2018-2019.

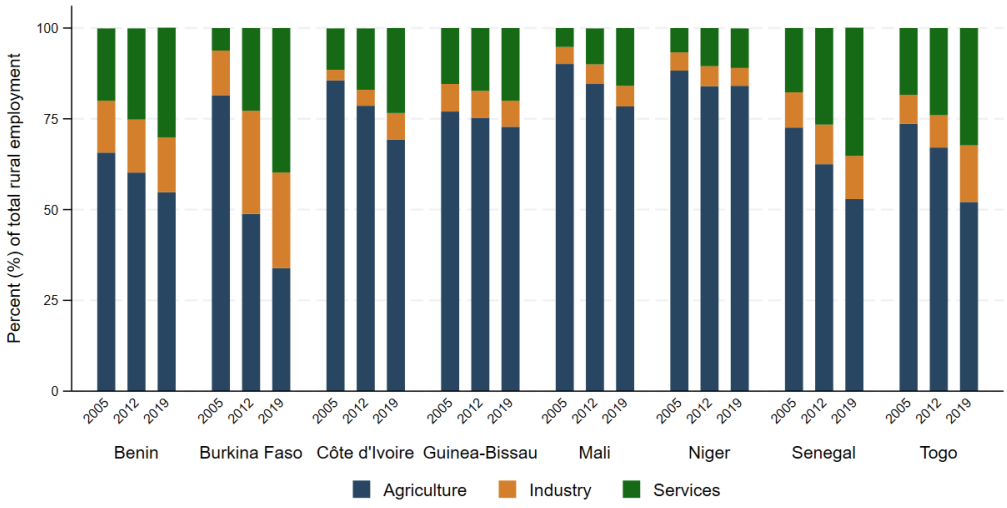
C. Changes in Agricultural, Off-Farm, and Non-Farm Activities

The proliferation of mobile technology in the WAEMU region is a factor that stands to influence significant changes in on-farm, off-farm, and non-farm activities. On-farm, mobile connectivity can facilitate better access to agricultural inputs and provide agricultural extension information about good agricultural practices. In theory, farmers can receive SMS or push-based advisories on best farming practices, pest management, and optimal planting times, which can contribute to improved crop yields. However, in practice, low literacy rates and poor innovation design often hamper use of digital agricultural extension services in many rural communities (Carroll, 2024; Abate et al., 2023, Aker & Cariolle, 2023).

[3] It should be noted that this statistic does not reveal the true percentage of the population with mobile access, as individuals in some households may have multiple mobile phone subscriptions while others have none.

Given the dependence on rainfed agriculture and the existence of a single rainy season per year in West Africa's drylands, non-agricultural activities are an increasingly important source of livelihood sustenance in the region. Figure I shows that the share of the rural population involved in the industry or services sectors has increased in all WAEMU countries from 2005 to 2019, although employment in agriculture was still over 75% for Mali and Niger in 2019 (ILO, 2024). Many households participate in non-farm wage or self-employment during the dry season as a means of generating increased income to support their agricultural production (Dedehouanou et al., 2018). Evidence from Burkina Faso, Tanzania, and Nigeria shows that non-farm self-employment and total non-farm employment have a positive impact on food and non-food expenditures (Gansonré, 2021, Bahia et al., 2021, 2024). Evidence from Niger shows that participation in unskilled non-farm employment is linked to increased agricultural spending on crop and livestock inputs, which suggests that non-farm activities are an important source of cash income that can support increased agricultural production (Dedehouanou et al., 2018).

FIGURE I. EVOLUTION OF RURAL EMPLOYMENT BY SECTOR IN WAEMU COUNTRIES



Source: ILO Modelled Estimates

II. Estimation Framework

A. The data

This study is based primarily on cross-sectional data from the Harmonized Survey on Households Living Standards (EHCVM)[4] for the eight member states of the West African Economic and Monetary Union (WAEMU). 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 EA level. The distribution of the sample in each country is shown in Table I below.

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 food expenditures and consumption patterns. Definitions and descriptive statistics of dependent variables are provided in Appendices A.1 and A.2, respectively.

Food product prices. 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, but only report in the main analysis the results associated with the first price record (Online Appendix D reports results obtained with the second record).

As prices for a given commodity are generally available for different non-standard units of measurement (e.g. small, medium, or large mound of chili peppers), we adopt two approaches. First, we consider, for each commodity, the log-transformed price of the

[4] Available at https://phmecv.uemoa.int/ or https://microdata.worldbank.org/index.php/catalog/lsms

commodity/measurement-unit pair most traded across EAs. District or region-commodity-unit fixed effects (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.[5] Second, 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 comparable estimates since all prices are expressed in XOF per gram.[6]

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

Demand for food products. We investigate the effect of digitalization on the demand for commodities, using i) food (and non-food) expenditures by households, and ii) quantities of food (self-)consumed and purchased, as dependent variables. The measurement of quantities (self-)consumed and purchased was made possible using 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.[7]

2. Mobile connectivity variables

We measure mobile connectivity through variables of spatial proximity to cell towers and adoption of mobile telephony. Access to internet is also addressed in a complementary manner in Section IV but is expected to be less pivotal in West African agricultural markets, because of low penetration of internet technologies in these areas (Abate et al., 2023; Aker & Cariolle, 2023). Appendix A.3 reports descriptive statistics of the digitalization variables described below.

Network connectivity. We use data on the spatial deployment of 2G+ cell towers from the OpenCellID project[8], and calculate two types of network connectivity variables:

- The logarithmic distance (in km) from the EA centroid to the nearest 2G+ tower.[9]

[5] 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 food product has been sold. See Online Appendix A.1.

[6] 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 consistency of estimated relationships.

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

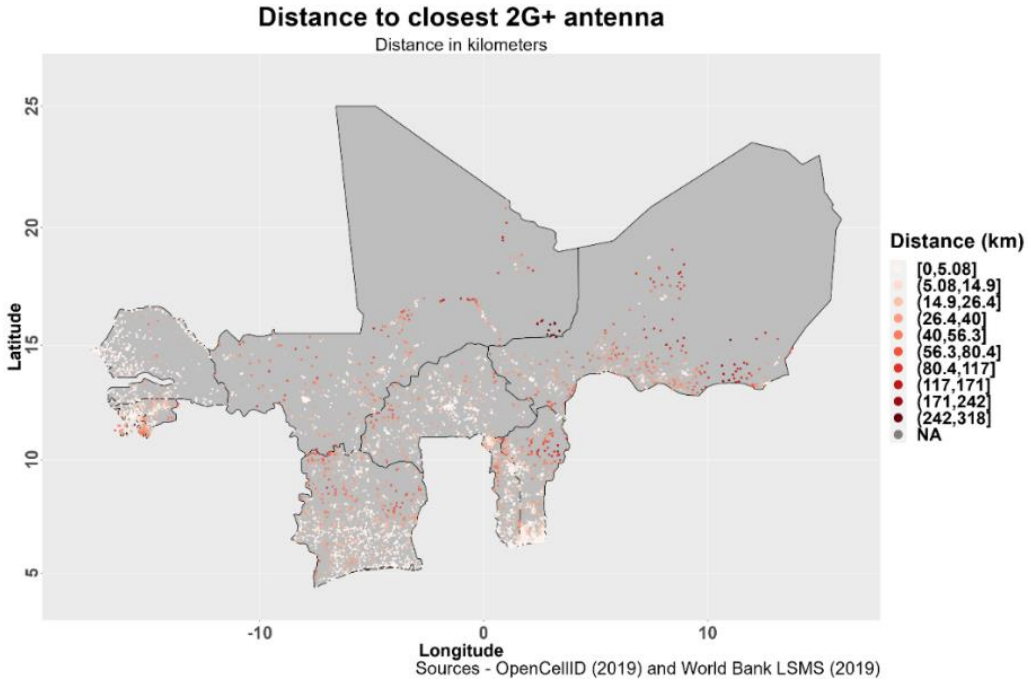
[8] https://www.opencellid.org/.

[9] 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 mobile network and internet access.

- A dummy variable equal to 1 if the EA centroid is within 2 km of the tower, 0 otherwise. We additionally compute a dummy variable equal to 1 if the EA centroid is within 5 km of the tower, 0 otherwise.[10]

On average, households are located in EAs located 14 km from the nearest 2G, 3G, or 4G (2G+) tower, and 51-56% of these HHs are located within a 2-5 km radius from the closest tower. When the analysis is carried out at the district level, i.e. when studying spatial price dispersion, we calculate the 2G+ coverage as a percentage of the district's surface area. Figure III maps the distance in kilometers from the center of surveyed EAs to the closest 2G+ cell tower.

FIGURE III. 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[11]), are found to play a pivotal role in agricultural and rural development (Abate et al, 2023; Aker & Cariolle, 2023).

[10] In robustness section V, we complement this measure by information on operator's network signal quality provided in LSMS dataset.

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

3. Control variables

We control for a number of determinants of local agricultural and rural development. These control variables and their associated descriptive statistics are shown in Online Appendices A.2 and A.3.

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, 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.), and the HH's farm characteristics (land area of rain-fed and irrigated plots).

EA-level controls. We control for local economic development by the density of nighttime lights, the presence of motorized collective transport in the EA, and by a set of dummy variables on the two main economic activities in the EA. We also control for demographic characteristics of the EA – i.e., population density in 2015, 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.

B. Empirical model and identification strategy

1. General model

In this study, we estimate the effect of digitalization ($DIG_{m,z,d}$) on food markets and HH livelihoods ($Y_{j,m,z,d}$). Food-product outcomes *j*, such as food-product prices or quantities, are observed at the HH *m*, EA *z*, or district *d* levels. Spending outcomes are observed at the HH level. The empirical analysis includes a number of control variables ($X_{m,z,d}$) and EA/district/region *z/d/r* (depending on the hierarchical level of the dependent variable), survey wave *v*, and product *j* FEs ($D_{z,d,r,v,j}$). Digitalization ($DIG_{m,z,d}$) is considered through the lens of infrastructure connectivity in the EA or district ($CON_{z,d}$) when the analysis is conducted at the EA or district level; 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 HH level.

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

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

$$DIG_{m,z,d} = G\left(CON_{z,d}; CON_z \times AD_m\right) \quad (1b)$$

whose calibration and scale of analysis is adapted to the outcome under consideration.

2. Identification strategy

The empirical analysis of the causal effect of mobile connectivity on rural development is weakened by a simultaneity bias – economic development 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 popularized by 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 higher deployment, repair and maintenance costs and lower connectivity quality (ITU, 2003; Martin 2016). Lightning-resistant protection for such equipment does exist, but it is still very costly and poorly deployed in SSA. Thus, 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 localized and counted at the grid-level by the Lightning Imaging Sensor, from January 1, 1998 to December 31, 2013 (Albrecht et al., 2016).[12] We follow a similar approach to Guriev et al. (2021) and weight this average by the population density in the EA, measured in 2015:

$$\text{Lightning_risk}_z = \text{Lightning_intensity}_z^{1998-2013} \times \frac{1}{1+\text{popdens}_z^{2015}} \qquad (2)$$

$\text{Lightning_intensity}_z^{1998-2013}$ is the average daily frequency of lightning strikes observed in EA z over the period 1998-2013, and $popdens_z^{2015}$ is 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, since averaging on a daily basis and over a 15-year period allows us to limit the influence of 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 expect that lightning strike exposure unrelated to these cyclical components matters more in operator decisions related to deploying new cell towers, and protecting and maintaining existing cell towers. Moreover, we also consider densely populated areas as a structural factor of network coverage that should be accounted for, since population density is associated with a higher demand for connectivity and economies of scale, and thereby expected to partially or fully reverse the adverse consequences of lightning strikes on the costs of deploying, protecting, repairing, and maintaining cell towers in lightning-exposed areas. Population density is therefore used as a weighting factor of lightning frequency (and additively as a control variable). A mapping of this variable is provided in Figure IV, which shows a lightning-strike belt mainly covering Côte d'Ivoire, Togo and Benin. Descriptive statistics for the weighted lightning IV, 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, more frequent fires, or power outages. First, our approach limits potential bias by constructing the instrument from de-seasonalized lightning data from the 1998-2013 period, hence years before the period of data collection used in the study. In addition, our estimations include spatial unit FEs, 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 nighttime light density in our

[12] Details given in Online Appendix A.4. Satellite data are only publicly available for years prior to 2013.

model, which controls for local economic development, and 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), which include droughts, irregular rains, floods, fires and landslides. Estimates remain robust and little affected by the inclusion or removal of these control variables, as shown in calibration tests reported in Online Appendix B.2.3. Importantly, we control in robustness analysis for contemporaneous and past rainfall, and conduct additional instrument validity tests, reported in Online Appendices E.3 to E.5. These tests support that identification is not conditional on observables and that the exclusion restriction is well respected.

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

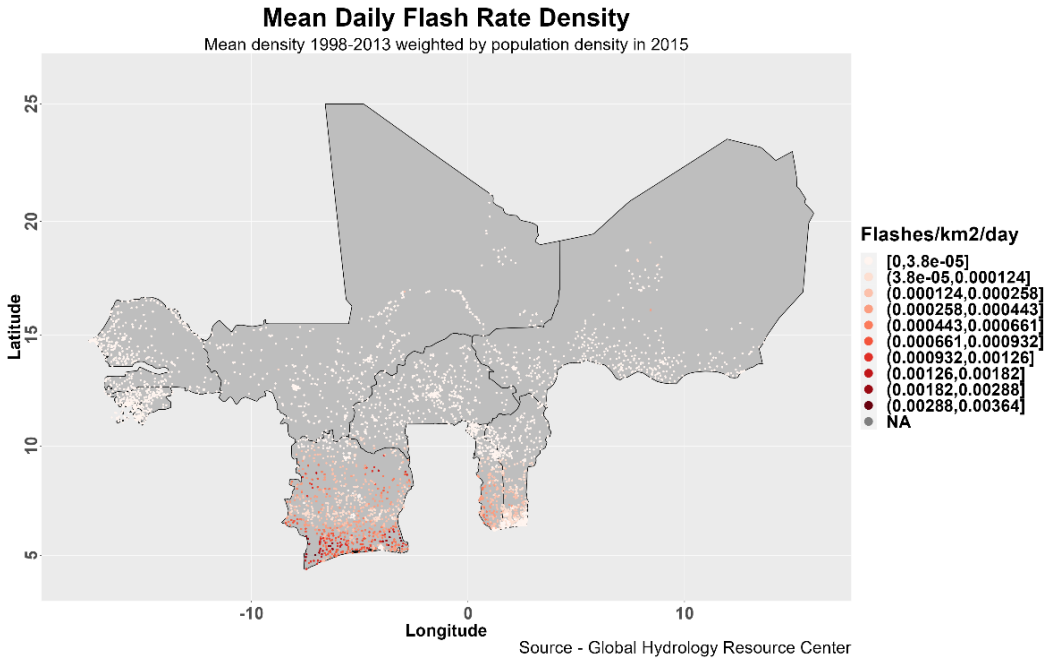


TABLE II. DESCRIPTIVE STATISTICS FOR INSTRUMENTAL VARIABLES.

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:

$$\mathrm{CON}_z = \alpha_0 + \alpha_1 . \mathrm{Lightning_risk}_z + \Gamma . \mathrm{X}_z + \Theta . \overline{\mathrm{M}_z} + \mathrm{D}_t + \mathrm{D}_d + \epsilon_z \qquad (3)$$

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. 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. D_d and 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.

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.[13] 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 5 km, see Online 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)).

TABLE III. EQUATION (3), OLS ESTIMATIONS.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	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	4,657	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

In this section, we show that mobile connectivity reduces food price dispersion by spurring food prices catchup in rural areas. While this result aligns with findings from smaller-scale studies focused on specific commodities, our analysis distinctly highlights the role of demand-side mechanisms in explaining price patterns across a broad range of food products.

A. Network connectivity and food product market prices

1. Baseline model

We start by investigating the effect of mobile network connectivity on food price levels. The following equation is estimated:

$$P_{z,j} = \beta_0 + \beta_1 . CON_z + \Gamma . X_z + \Theta . \overline{M_z} + D_t + D_{d,j} + \varepsilon_{z,j} \qquad (4)$$

$P_{z,j}$ is either the natural logarithm of the price of a commodity-unit pair *j*, termed "non-converted food price", or the price of a commodity-unit pair converted into XOF per gram using

[13] Details of the estimates for the control variables are given in Online Appendix B.1.

measurement-unit conversion factors[14]. CON_z is the connectivity variable in EA z. X_z and $\overline{M_z}$ are EA-level controls and HH level controls averaged at the EA level.

Initially, the analysis is conducted on the price levels of commodity-measurement unit pairs most commonly traded in EAs.[15] We introduce FEs for each district commodity-measurement unit combination (e.g. small/medium/large heap of fresh tomatoes), $D_{d,j}$, to capture district-level unobserved characteristics, 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 network connectivity on the level of multiple commodity prices. Estimates with alternative calibrations are reported in Online Appendix B.2.3.

Alternatively, we use the price of all commodity-unit pairs traded in EAs converted in XOF per gram, using non-standard measurement-unit conversion factors, and controlling for district and product-unit FEs. While this conversion makes prices directly comparable, it comes at the risk of introducing statistical noise if conversion factors are mismeasured.[16]

2. Price levels

Table IV presents baseline 2SLS estimations of equation (4).[17] OLS estimates, 2SLS estimates with alternative FE calibrations, and 2SLS estimates with the second price record are reported in Online Appendices B.2.1, B.2.3, and D, respectively. The first-stage statistics rule out the risk of weak instrument bias.

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)). Estimates obtained 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 centroid increases the general level of food prices within these EAs by around 10-12%. These estimates lie within the same range as those provided by reference studies on using similar connectivity measures (Jensen, 2007; Svensson & Yanagizawa, 2009; Aker, 2010; Goyal, 2010: Aker & Fafchamps, 2015), which tends to confirm their relevance.[18] Estimates using the converted food prices are consistent with baseline estimations, albeit slightly less significant.

Estimates obtained from other model calibrations and alternative price records provided in Online Appendices B.2.3 and D.1 are also consistent with baseline estimates. Marginal effects of network connectivity on the price level of each of the most-traded products are reported in Online

[14] Price variables used in the main analysis are based on the first record of food product's prices. Estimations using the second record of food product prices are reported in Online Appendix D.

[15] 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 trading frequency.

[16] See Online Appendix C for details on the conversion of non-standard measurement units.

[17] Only interest variable estimates are reported. Detailed estimates of control variables are provided in Online Appendix B.2.2.

[18] See the literature review in Online Appendix F, and Aker and Cariolle (2023) for an extensive review of these studies.

Appendix B.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 general level of commodity prices in connected areas was observed, the effect of connectivity was nevertheless heterogeneous according to the type of commodity considered.

TABLE IV. EQUATION (4), 2SLS SECOND-STAGE ESTIMATIONS.

Dep. Var.: price record 1	(1)	(2)	(3)	(4)	(5)	(6)
	NC price (ln, XOF)			C prices (XOF/gram)		
Distance 2G+ (ln, km)	-0.037***			-0.060*		
	(0.011)			(0.034)		
Dist. 2G+ <2km (0/1)		0.111***			0.175*	
		(0.035)			(0.098)	
Dist. 2G+ <5km (0/1)			0.103***			0.175*
			(0.032)			(0.097)
Controls (X_z; $\overline{X_m}$)	Yes	Yes	Yes	Yes	Yes	Yes
District-prod-unit FE	Yes	Yes	Yes	No	No	No
District FE	No	No	No	Yes	Yes	Yes
Prod-unit FE	No	No	No	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,740	129,670	129,687	356,603	356,494	356,468
AR F-test (p-val.)	0.00075	0.0008	0.0007	0.0658	0.0654	0.0647
KP Wald F-stat	67.23	47.24	65.34	71.12	56.79	61.64
KP rank LM-stat	47.52	31.70	29.50	40.79	27.20	23.72

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. Price convergence

If the positive effect of connectivity on prices is explained by a greater demand for food products from connected households, the resulting effect on price dispersion remains uncertain, as it may depend on where increases in food demand occurred. Therefore, we explore the spatially heterogenous connectivity effect on price in urban and rural areas, by augmenting the basic econometric model with an interaction term between the connectivity variable (CON_z) and urban location (URB_z).

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

URB_z is a variable taking the value of 1 if the EA is an urban area, 0 otherwise. CON_z is a dummy variable indicating whether an EA centroid is located within a 2 km radius from a cell tower. We instrument the connectivity variable and the interaction term by the instrument alone and also the interaction between the instrument and the urban area dummy variable. Results, reported in Table V (columns (1)-(2)), show that proximity to mobile network towers raises food prices by an average of 15% in rural areas, while its effect is substantially smaller in urban areas (+3.3%).

Next, we explore the hypothesis of food price catchup in rural areas, by replacing the price variable by the absolute deviation between a product's (converted) price and its average price in

district's urban areas[19]. We re-estimate equation (5) using this new dependent variable, splitting the sample into EA-product pairs where the price gap is negative (columns (3) and (4)) and those where it is positive (columns (5) and (6)). The analysis reveals a reduction in the absolute deviation for connected rural areas where the price gap is negative, suggesting that food price catch-up has occurred in these areas. They also highlight a divergence, reflected by an increase in the absolute deviation, in urban areas when the price gap is positive, but this effect appears to be less robust.

TABLE V. EQUATION (5), 2SLS SECOND-STAGE ESTIMATIONS.

Dep. Var.: price record 1	(1)	(2)	(3)	(4)	(5)	(6)
	NC prices	C prices	Absolute dev. from average urban C prices (%)			
			Urban price gap < 0		Urban price gap > 0	
			Excl. top 5%	Excl. top 1%	Excl. top 5%	Excl. top 1%
Dist. 2G+ <2km (0/1)	0.152***	0.268*	-0.105***	-0.100***	-0.030	-0.020
	(0.039)	(0.140)	(0.020)	(0.020)	(0.020)	(0.036)
Dist. 2G+ <2km × urban (0/1)	-0.119***	-0.363*	0.114***	0.109***	0.087***	0.061*
	(0.046)	(0.201)	(0.026)	(0.025)	(0.021)	(0.035)
Controls (X_z; $\overline{X_m}$)	Yes	Yes	Yes	Yes	Yes	Yes
District-prod-unit FE	Yes	No	No	No	No	No
District FE	No	Yes	Yes	Yes	Yes	Yes
Prod-unit FE	No	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,670	353,495	189,282	190,698	149,175	160,228
AR F-test (p-val.)	3.84e-05	0.112	3.12e-06	7.29e-06	0.000101	0.154
KP Wald F-stat	23.78	27.54	27.34	27.40	31.05	31.24
KP rank LM-stat	37.73	37.09	38.85	38.30	38.16	37.89

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. First price record used in this analysis. C/NC stands for converted/non converted.

4. Price dispersion

Third, 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:

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

$\mathrm{CV_{d,j}}$ is the coefficient of variation of the price of food commodity *j* observed in the EAs (in %), calculated at the district level *d*. $\overline{\mathrm{X_d}}$ and $\overline{\mathrm{M}_d}$ are the sets of EA- and HH-level controls, averaged at the district level, excluding EA topography variables. $\mathrm{D_{r,j,u}}$ 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.

Results are reported in Table VI. Estimates in column (1) do not support any significant effect on price dispersion. However, the Anderson-Rubin test points to the weakness of our instrument. It

[19] Computed as, $abs\left(\frac{\mathrm{P_{z,j}}-\overline{P_{d,J}}}{\overline{P_{d,J}}}.\right)$, and excluding top 5% or 1% values to neutralize the influence of extreme values.

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. Therefore, we re-estimate equation (6) using the raw (unweighted) average number of lightning strikes at the district level (column (2) and (3)). In columns (4) and (5), we additionally control for the averaged level of product prices, to account for a potential direct relationship between the coefficient of variation and price levels.

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.

TABLE VI. EQUATION (6), 2SLS SECOND-STAGE ESTIMATIONS.

Dep. Var.: CV_{dju} (%)	(1)	(2)	(3)	(4)
Price record 1:		NC price		C price
2G+ coverage (%)	0.038	-0.518**	-0.524**	-0.491*
	(0.400)	(0.205)	(0.205)	(0.278)
Ln $P_{d,j}$			0.000***	0.008**
			(0.000)	(0.004)
Instrument:	Pop-weighted	Raw lightning strikes		
Controls	Yes	Yes	Yes	Yes
Region-prod. FE	Yes	Yes	Yes	Yes
Observations	19,399	19,399	19,399	19,399
AR F-test (p-val.)	0.924	0.00598	0.00694	0.00518
KP Wald F-stat	32.66	41.82	41.82	41.77
KP rank LM-stat	54.72	41.51	41.51	41.47

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.

5. The demand channel

Evidence of price catch-up in rural areas, along with price divergence in urban areas where prices exceed the average, suggests that supply-side reallocation mechanisms—from oversupplied to undersupplied areas or *vice versa*—are unlikely to explain reduced price dispersion. This underscores that factors other than supply shifts are influencing price movements, with adjustments in rural areas appearing more directly related to demand dynamics.

Therefore, we test the demand channel by including in equation (4) the interaction term between the mobile network proximity dummy and total food expenditures in the EA[20], controlling additionally for non-food expenditure variables. Results are presented in Table VII below. They support the relevance of the demand channel, since the interaction between proximity to a mobile network and food expenditures is positive and significant, while standalone expenditure variables are either negative or zero. Following up on this evidence, the next subsection further addresses the impact of mobile connectivity on HH demand for food products.

[20] 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.

TABLE VII. NETWORK CONNECTIVITY AND THE DEMAND CHANNEL, 2SLS SECOND-STAGE ESTIMATES.

	(1)	(2)
Dep. var: Price record 1	NC prices (ln, XOF)	C prices (XOF/gram)
Dist. 2G+ <2km (0/1)	-0.424**	-0.963
	(0.185)	(0.656)
Dist. 2G+ <2km (0/1) × EA food spend.	0.026***	0.056*
	(0.010)	(0.033)
EA food spend. (XOF, ln)	-0.014	0.096
	(0.009)	(0.063)
EA non-food spend. (XOF, ln)	-0.001	-0.133*
	(0.008)	(0.068)
Controls	Yes	Yes
District-prod-unit FE	Yes	No
District FE	No	Yes
Prod-unit FE	No	Yes
Survey wave FE	Yes	Yes
Observations	129,670	356,496
AR F-test (p-val)	0.00033	0.0855
KP Wald F-stat	24.56	29.09
KP rank LM-stat	31.35	26.74

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 HH level, focusing on HH spending on both food and non-food products, as well as on the quantities of food commodities consumed, purchased, and self-consumed.

1. Baseline model

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. 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.

We investigate the effect of owning mobile phones (AD_m)[21] in EAs covered by the mobile network (CON_z) on HH (food) expenditures, and on the quantities of food commodities (self-)consumed or purchased by these households ($DEM_{m(j)}$):

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

[21] Since digitalization in African rural areas mostly relies on feature phone access (Aker & Cariolle, 2023), we focus on HH mobile phone adoption, leaving the analysis of internet adoption for the robustness section.

Where the interaction term ($\mathrm{CON_z} \times \mathrm{AD_m}$) is instrumented by our initial instrument interacted with the number of cell phones in the household m (AD_m).[22] $DEM_{m(j)}$ is by sequencing order:

i) a set of expenditure variables – food and non-food – per HH member (XOF, ln).
ii) the quantity of a commodity *j* consumed, self-consumed, and purchased per HH member (grams, ln).

Variable definitions and descriptive statistics are provided in Appendix A.2. CON_z is a dummy for the 2 km-proximity to the nearest 2G, 3G or 4G tower.[23] M_m is the set of baseline HH control variables, to which is added a dummy for internet access in the home or outside the home. $\omega_{m(j)}$ is an error term. D_z, D_t, and D_j are respectively EA, survey wave, and product-unit FEs.

Interacting the instrumented network connectivity with a digital technology adoption variable could lead to bias arising from the simultaneously causal relationship between digital technology adoption and demand for food products. This bias should be limited, but not fully ruled out, by additively controlling for mobile and internet adoption by HHs and also for a large range of HH characteristics (Online Appendix A.2) which could both explain mobile adoption and food consumption.

2. Household spending

Firstly, we investigate the effect of mobile connectivity on HH food spending. We estimate equation (7) using food expenditure per HH member as the dependent variable, and additionally controlling for non-food expenditures.[24] Results are reported in Table VIII. To prevent overfitting bias with EA FEs, we also estimate equation (7) using district level FEs (column (2)). This approach has the advantage of simultaneously estimating the effect of network proximity for mobile owners (A) and the network externality for non-owners (B).[25] We also run estimations splitting the sample between urban and rural HHs (columns (3) and (4)).

Estimations indicate that owning an additional mobile phone in connected areas leads to a 13% increase in HH food expenditures per household member (column (1)), with the effect being significantly stronger in rural areas, where expenditures per person increase by 37% (column (4)). Estimates are also consistent across calibrations (column (2) and Online Appendix B.4.1) suggesting that the risk of omitted variable and overfitting biases is limited. Interestingly, the estimate of the standalone connectivity variable (variable (B)) stresses that improved network coverage reduces per-HH member food expenditures in non-covered HHs by 28%, suggesting the presence of a negative externality that could be related to rising food prices evidenced in the previous section.[26]

[22] The instrument interacts as follows: $\mathrm{IV_m} = \mathrm{Lightning_risk_z} \times \mathrm{AD_m}$.

[23] For the sake of simplicity, we focus the remaining analysis on this network proximity variable. Estimates using alternative connectivity variables are available in Cariolle and Carroll (2024).

[24] Removing this additional control does not affect the sign and significance of estimates, only their magnitude.

[25] Alternative calibrations provide robust and consistent estimates. See Online Appendix B.4.1

[26] Additional estimations presented in Online Appendix B.4.2 highlight a smaller increase in non-food expenditures (+6%), driven by rural areas only (+34%). The estimated effect of the standalone connectivity variable (variable (B)) is not significant, thereby giving additional credit to the possibility of a negative externality of connectivity resulting from food price increase.

Moreover, consumption patterns are not altered by the inclusion of total HH farm revenues as a control, despite sample attrition generated by inclusion of this variable (see Online Appendix B.4.3). This suggests that this demand-side effect is not driven by increased farm revenue due to higher food-product prices.

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

Dep. Var.: food spending per cap. (XOF, ln)	(1)	(2)	(3)	(4)
	All EAs		Urban EAs	Rural EAs
(A) Dist. 2G+ <2km (0/1) × # mob.	0.128***	0.117***	0.110**	0.375***
	(0.030)	(0.031)	(0.048)	(0.145)
(B) Dist. 2G+ <2km (0/1)	-	-0.289**	-	-
	-	(0.138)	-	-
HH controls	Yes	Yes	Yes	Yes
EA controls	No	Yes	No	No
EA FEs	Yes	No	Yes	Yes
District FEs	No	Yes	No	No
Survey wave FEs	Yes	Yes	Yes	Yes
Observations	56,817	55,466	23,220	33,597
AR F-test (p-val.)	1.22e-05	0.000148	0.0321	7.03e-05
KP Wald F-stat	102.2	14.57	47.68	12.13
KP rank LM-stat	67.63	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 (2) to (5), (A) and (B) are instrumented by the lightning strike IV and the lightning strike IV interacted with the number of mobile phones in the HH.

3. Household (self-)consumption

Secondly, we estimate equation (7) using the quantity of food products consumed (C), purchased (P), and self-consumed (SC) per HH member as dependent variables, additionally controlling for the diversity of commodities consumed in the HH.[27] 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. The acquisition of a cell phone by a HH living in a connected area contributes to a 20% increase in quantities of food consumed, and a 29% increase in quantities of food purchased. There is spatial heterogeneity in these effects, as urban areas experienced a lower increase in consumed and purchased quantities (+23%; +29%) than rural ones (+41%; +61%).

Additionally, mobile connectivity reduces HH reliance on self-consumption, particularly for rural HHs. In fact, we observe a 9% reduction in the quantity of self-consumed products by connected HH compared to non-connected ones. This effect is stronger in rural areas (-19%) than in urban areas (-7%).

[27] Measured by the number of different product types consumed by the HH. Although in enters significantly in the model, removing this additional control does not change the results.

In Online Appendix B.5, we also report the marginal effects of mobile connectivity on the quantities consumed of each of the 15 commodities most consumed by HHs. The results show an overall significant and positive effect of connectivity 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). We observe a marked positive impact for peanut oil, salt, sugar, fermented locust bean, coffee, and bouillon cubes.

In sum, increased market demand for food products therefore appears to be an important driver of food prices convergence between rural and urban areas. Moreover, estimations highlight a negative externality of mobile connectivity on HHs located in connected areas but without mobile phones, suggesting that the latter suffer from rising food prices without benefiting from the increase in purchasing power associated with digitalization.

TABLE IX. MOBILE CONNECTIVITY AND QUANTITY OF COMMODITIES (SELF-) CONSUMED AND PURCHASED PER HH MEMBER, 2SLS SECOND-STAGE ESTIMATES.

	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)	(10)
Dep. var.: quant. per	All EAs			Urban EAs			Rural EAs		
cap. (grams, ln):	C	P	SC	C	P	SC	C	P	SC
Dist. 2G+ <2km (0/1)	0.196***	0.288***	-0.088***	0.226***	0.295***	-0.073*	0.406***	0.610***	-0.186**
x # mob.	(0.023)	(0.026)	(0.027)	(0.042)	(0.044)	(0.042)	(0.075)	(0.108)	(0.088)
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
Product-unit FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	950,458	757,790	1,153,711	480,658	415,375	555,821	469,374	342,021	597,352
AR F-test (p-val.)	0	0	0.00143	4.07e-07	1.4e-10	0.0727	0	0	0.0310
KP Wald F-stat	323.4	336.3	318.3	153.1	144.3	153.4	59.07	54.06	36.71
KP rank LM-stat	212	254	215	91	81.49	86.37	47.33	48.44	31.21

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. Results are also robust to clustering at the EA level and can be provided upon request.

IV. ADDITIONAL EVIDENCE

In this section, we explore the contribution of mobile-enabled services, i.e. internet access and mobile money, as well as off-farm income and nonagricultural entrepreneurship, in explaining food demand 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 (Ayalew et al., 2022; Abate et al., 2023). We therefore re-estimate equation (7) by interacting the network connectivity variable with the internet adoption dummy, which was ultimately included as a standalone control variable.

Estimates are reported in Appendix B.1. The impact of internet access, despite being consistent with estimated effects of mobile phone access in general, is found to be more moderate and less robust, probably due to the high cost associated with internet access and the lower absorption capacity of internet-based technologies by (rural) populations.[28] 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 (Suri et al, 2023). 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.

In the WAEMU, mobile money is the privileged tool for financial inclusion compared to other financial services, as 34% of surveyed HHs are found to own at least one MM account (Appendix B.2.1). We test the moderating effect of MM adoption on food demand by first including in equation (7) a MM ownership variable dummy as an interaction term, alone or together with mobile phone adoption to identify the respective contribution of mobile telephony and mobile money account ownership.

Results, presented in Appendices B.2.2 to B.2.4, show that part of the effect of mobile connectivity on food demand is moderated by HH access to MM. Appendix B.2.2 shows that MM account ownership increases HH food spending by 17% (column (3)), by 32% in rural areas (column (5)), with no significant effects observed in urban areas (column (4)). Moreover, accounting for the effect of mobile money lowers the positive effect of mobile phone connectivity on food spending by 3.1 percentage points, as reported in column (1)).

Similar demand patterns are evidenced when focusing on the quantities of food products consumed and purchased by HH members. Results, reported in Appendix B.2.3, show that part of the positive effect of mobile money on food consumption (+12%) is driven by rural HHs (+28%). A positive effect of MM on food purchases is also evidenced (Appendix B.2.4), but only in rural areas (+22.5%). Overall, this evidence suggests that MM is therefore a mobile-enabled technology that has likely contributed to food price catchup in rural areas and reduced food price dispersion, through its effect on food purchases.

[28] Similar evidence is obtained when restricting the variable on EA distance from mobile networks to 3G and 4G networks only. Results can be provided upon request.

B. On-farm and 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[29], while nonagricultural entrepreneurship is measured by the number of nonagricultural enterprises created within the HH. The following model is estimated:

$$JOB_m = \delta_0 + \delta_1 . \mathrm{CON_z} \times \mathrm{AD_m} + \delta_2 . \mathrm{AD_m} + \Gamma . \mathrm{M_m} + \mathrm{D_z} + \mathrm{D_t} + \omega_\mathrm{m} \quad (8)$$

When studying nonagricultural entrepreneurship, we additionally control for the time passed since the first enterprise was created within the HH.[30] Results, reported in Appendix D.3.1, show mobile connectivity respectively increases the share of HH members earning off-farm and on-farm incomes by 9% and 6%, respectively, supporting that connectivity increases the relative share of HH members engaged in off-farm revenue-generating activities. Moreover, these effects are stronger for rural HHs (+27%; +17%) compared to urban ones. Estimations conducted on the number of nonagricultural enterprises are reported in Appendix D.3.2 and support the hypothesis 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 spurred by improved access to off-farm and non-agricultural revenues in rural areas.

[29] A HH member is considered to be engaged in on-farm activity if she/he worked at least one hour in 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.

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

V. ROBUSTNESS CHECKS

A. Mobile network quality

Our connectivity measure, based on distance to cell towers as reported in the OCI database, may be an imprecise measure of the 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 differ in size, meaning that a given distance from the centroid of an EA to the closest cell tower may reflect varying actual distance to a cell tower for surveyed HHs, 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 these data with community-level LSMS survey data on the number of well-captured mobile networks in each EA. Thence, we construct the following mobile network variables:

- Dummy variables equal to one if at least one, two, or three mobile networks are well-captured within 2 km from the closest cell tower.
- The number of mobile networks well-captured within 2 km 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 Online Appendix E.1.[31] They confirm the robustness of our results and show that the greater the network quality, the stronger the impact of mobile connectivity on food markets and rural livelihoods.

B. Sensitivity and instrument validity tests

1. Spatial anonymization

Second, 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 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 Online Appendix E.3.1, to build our instrumental variable. Results, reported in Online Appendixes E.2.2 and E.2.3, are robust to this first sensitivity test.

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

2. Reduced-form estimations

Third, 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 Online Appendix E.3, have the expected sign and confidence intervals. 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 Online Appendix E.3.1. Density and IV estimates remain stable across estimations suggesting that they do not suffer from this source of bias.

3. The exclusion restriction assumption

Fourth, 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 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 Online Appendix E.4.1, we estimate baseline equation (4), additionally controlling for daily precipitation (Beck et al., 2019) in the EAs averaged over 2018 or 2019 (columns (1) and (2)), as well as for lagged precipitation averaged over 2017 (columns (3) and (4)), or over the 2015-2019 period (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.

In addition, 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 sub-section III.A.5, over the instrument and population density (columns (1) to (3)), and then including distance to the network as a control variable (columns (4) to (6)). Results in Online Appendix E.4.2 show a negative and significant effect of lightning strikes on spending variables, which turns 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 is explained by reduced mobile network connectivity. Therefore, these tests provide additional credit to the absence of any exclusion restriction violation.

4. Network externality, mobile spillovers and the SUTVA

Fifth, the SUTVA would be violated if the response of a particular HH would be affected by the response of neighboring HHs to improved connectivity, or if adoption of a mobile phone by a HH would deteriorate the livelihoods of non-adopters located in the same communities. 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 Table VIII and Online Appendix B.4.1. Additionally, we control for mobile spillover effects on non-adopters and

adopters, by respectively including the share of HHs 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 HH food expenditures and food consumption per capita as dependent variables, and report estimates in Online Appendix E.5.1.

Results show that the effect of mobile ownership in connected areas (A) is robust to controlling for digital spillovers ((C) and (D) and relatively stable across estimations. They also confirm that HHs without mobile phones in connected EAs 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 (B). Regarding mobile adopters, 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). Finally, non-adopters appear to benefit from positive spillover effects from the local diffusion of mobile phones in the EA (D).

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 levels are displayed in Online Appendix E.5.2. 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%). Another plausible explanation is the loss of strength in the IV resulting from its spatial distribution, which is heavily concentrated in Côte d'Ivoire. Nevertheless, the instrument regains strength and the estimated effect returns to a comparable size and acceptable significance level when levelling-up the FEs from the district-product level 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 paper explores interconnected dimensions of agri-food systems influenced by the diffusion of mobile phones across West Africa, including price levels and dispersion, household food expenditures and consumption patterns, financial inclusion, and access to off-farm and non-agricultural income sources.

Our analysis shows that mobile network extension in the WAEMU region has reduced food price dispersion, by spurring food price catchup in connected rural locations. While this evidence aligns with the findings from smaller-scale studies focused on specific countries and commodities, our analysis distinctly highlights the role of demand-side mechanisms in explaining price patterns across a broad range of food products. We indeed find that mobile connectivity not only increases market demand for food products but also reduces self-consumption among connected rural households. Specifically, our results indicate that income diversification through off-farm activities and non-agricultural entrepreneurship and financial inclusion via mobile money adoption are significant drivers of the observed convergence in food prices. These dynamics suggest that the narrowing of food price dispersion is a reflection of broader rural transformations, not only the result of improved supply allocation mechanisms or increased bargaining power among connected farmers.

Therefore, our analysis underlines the need to promote digitalization policies in rural areas beyond the strict support to the agricultural sector, considering complementary markets such as the financial or labor markets in their design. It also suggests the importance of continued efforts to extend network coverage and improve its quality, but also to encourage increased digital absorption capacity of households, especially those located in rural areas. While our results highlight clear benefits for food market functioning and rural livelihoods in connected areas, they also point to the risk of impoverishment of poorly digitalized households facing rising food prices in those same areas. Thus, the usage gap, in addition to 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.

APPENDIX

A. Variable definitions and descriptive statistics

A.1. Dependent variable definitions.

Dependent variable:	Mathematical expression	Obs. unit
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
Logarithm of the quantity in gram of a given commodity consumed by a household member m in the 7 days preceding the survey.	Ln $QCO_{j,m}$	HH-product
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
Logarithm of the quantity in gram 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} *	**Observation unit: EA-product**				
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	3,444	0.42	0.40	0.15	22.81
$CV_{d,j}$ (all prod.)	**Observation unit: District-product**				
Unconverted price	19,363	0.21	0.24	0	3.598
Converted price	25,837	0.40	0.34	0	5.320
Ln $QPU_{h,j}$	**Observation unit: HH-product**				
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

Ln $QCO_{h,j}$*					
	Observation unit: HH-product				
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
HH spending, ln XOF		**Observation unit: HH**			
Ln $CONSF_m$	59,318	12.13	0.71	8.55	15.99
Ln $CONSNF_m$	59,318	11.96	0.85	8.89	16.44

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

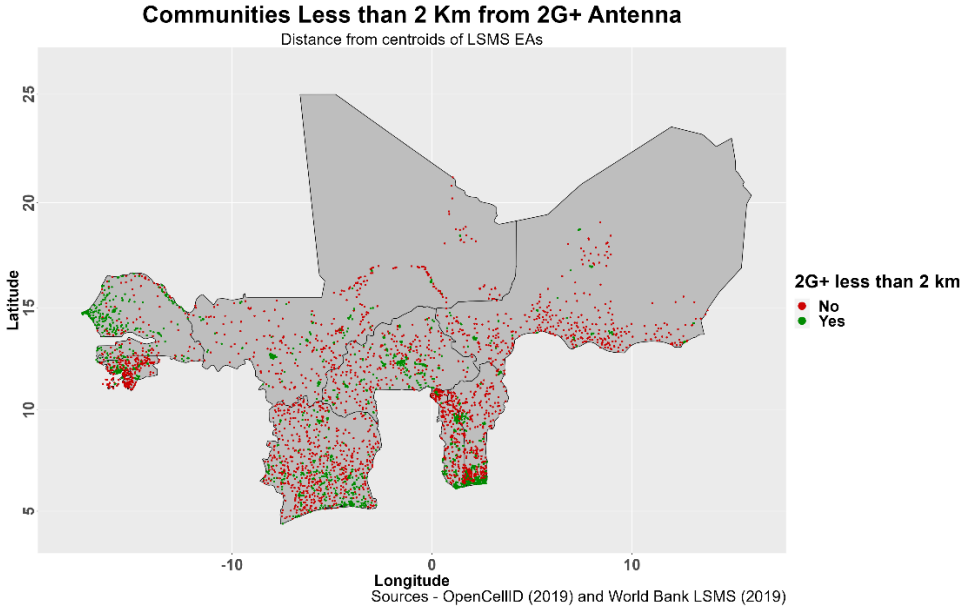
A.3. Digitalization variables

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	318.1
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)	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, included for comparison purpose.

A.3.2. Mapping of the dummy variable of EAs located within 2 km of the nearest cell tower.



B. Additional estimations

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

B.1.1. Internet connectivity and food expenditure per HH member, 2SLS estimates.

Dep. var: Food exp per cap (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)
	All EAs		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)
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. Other control variable estimates not reported. EA and survey wave FEs included.

B.1.2. Internet connectivity and quantities (self-)consumed per HH member, 2SLS estimates.

Dep. Var.: quantities consumed per cap (grams, ln)	(1)	(2)	(3)	(4)	(5)	(6)
	All EAs		Urban EAs		Rural EAs	
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)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA & Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Food prod.-unit FEs	Yes	Yes	Yes	Yes	Yes	Yes
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

Standard errors in brackets, robust to heteroskedasticity and clustered by HH. * p < 0.1, ** p < 0.05, *** p < 0.01. Other control variable estimates not reported.

B.1.3. Internet connectivity and quantities purchased per HH member, 2SLS estimates.

Dep. Var.: quantities purchased per cap (grams, ln)	(1)	(2)	(3)	(4)	(5)	(6)
	All EAs		Urban EAs		Rural EAs	
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 & Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
Food prod.-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.

B.2. Financial inclusion and mobile money ownership.

B.2.1. Financial inclusion in the WAEMU

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

B.2.2. Financial inclusion and HH food expenditures

Dep. Var: food exp. pc (XOF, ln)	(1)	(2)	(3)	(4)	(5)
	All EAs			Urban	Rural
Distance 2G+ <2km (0/1) x nb.tel	0.128***		0.097***	0.095**	0.318**
	(0.030)		(0.029)	(0.048)	(0.144)
Distance 2G+ <2km (0/1) x MM		0.212***	0.174**	0.063	0.320*
		(0.067)	(0.068)	(0.105)	(0.185)
MM account owner (0/1)		-0.174***	-0.151***	-0.099	-0.166***
		(0.039)	(0.039)	(0.093)	(0.064)
Nb. Mobile phones	-0.075***	0.011***	-0.054***	0.012	-0.033
	(0.020)	(0.003)	(0.019)	(0.011)	(0.024)
HH controls	Yes	Yes	Yes	Yes	Yes
EA & Survey wave FEs	Yes	Yes	Yes	Yes	Yes
Observations	56,188	56,188	56,188	22,988	33,200
AR F-stat	1.24e-05	0.00103	1.89e-05	0.127	9.06e-05
KP Wald F-stat	101.6	108.8	50.02	24.52	5.461
LM-weak	67.11	69.61	66.16	21.58	8.814

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01. Other control variable estimates not reported.

B.2.3. Mobile money and quantities consumed per HH member, 2SLS estimates

Dep. Var.: quantities consumed per cap (grams, ln)	(1)	(2)	(3)	(4)	(5)	(6)
	Consumed commodities			Self-consumed commodities		
	All	Urban	Rural	All	Urban	Rural
Dist. 2G+ <2km (0/1) x nb.tel	0.155***	0.187***	0.333***	-0.091***	-0.077*	-0.184**
	(0.022)	(0.041)	(0.073)	(0.028)	(0.044)	(0.094)
Dist. 2G+ <2km (0/1) x MM	0.120***	0.073	0.281***	-0.023	0.010	-0.158
	(0.040)	(0.062)	(0.099)	(0.054)	(0.082)	(0.139)
MM account owner (0/1)	-0.222***	-0.209***	-0.255***	0.026	0.005	0.087
	(0.027)	(0.056)	(0.044)	(0.035)	(0.071)	(0.056)
Nb. Mobile phones	-0.104***	-0.168***	-0.123***	0.002	0.001	0.008***
	(0.017)	(0.039)	(0.031)	(0.001)	(0.001)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
EA & 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.)	0	4.84e-05	0	0.00272	0.185	0.0270
KP Wald F-stat	162.5	80.24	28.56	159.2	80.50	17.30
KP rank LM-stat	211.8	93.72	45.67	215.7	88.26	29.67

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01. Other control variable estimates not reported.

B.2.4. Mobile money and quantities 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 nb.tel	0.249***	0.259***	0.531***
	(0.025)	(0.043)	(0.102)
Distance 2G+ <2km (0/1) x MM	0.055	0.003	0.225**
	(0.043)	(0.069)	(0.109)
MM account owner (0/1)	-0.276***	-0.275***	-0.367***
	(0.030)	(0.060)	(0.045)
Nb. mobile phones	0.010***	0.010***	0.019***
	(0.002)	(0.003)	(0.003)
Controls	Yes	Yes	Yes
EA & Survey wave FEs	Yes	Yes	Yes
Observations	749,176	411,346	337,437
AR. F-test (p-val.)	0	4.65e-08	0
KP Wald F-stat	171.2	75.85	26.53
KP rank LM-stat	253	83.65	47.11

Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01. Other control variable estimates not reported.

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

B.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 & Survey wave 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. Other control variable estimates not reported.

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

Dep. Var: # of non-agricultural enterprises in the HH	(1) All	(2) Urban	(3) Rural
Dist. 2G+ <2km (0/1) x # mob.	0.113**	0.096	0.266*
	(0.045)	(0.111)	(0.148)
Years since first enterprise creation	0.027***	0.018***	0.032***
	(0.001)	(0.001)	(0.001)
Controls	Yes	Yes	Yes
EA & Survey wave 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. Other control variable estimates not reported.

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A. Additional descriptive statistics

A.1. Most-traded product-unit pairs: number of EAs trading the product-unit pair.

Product-unit pairs ordered by trading 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.2. 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.3. 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.4. Raster Dataset Specifications:

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 Online Appendix D.3.

A.4.1. 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.4.2. 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.4.3. 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.5. 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. 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

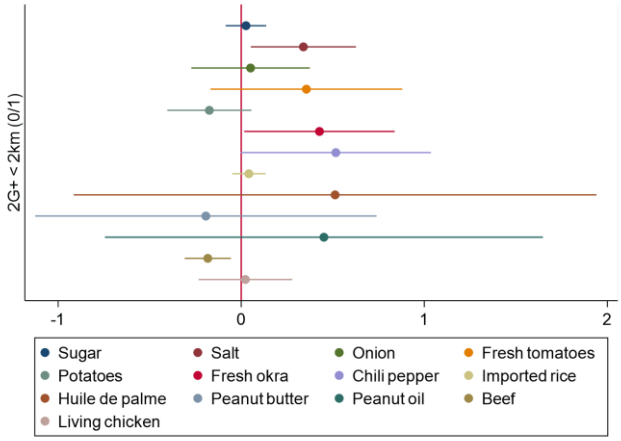
Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01..

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

Dep. Var: Ln P_{zi} (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 (%)	CV price 2	2G+ cov (%)
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)
# EAs (Ln)	0.009	0.027***	0.012	0.027***
	(0.009)	(0.004)	(0.009)	(0.004)
Elec. Network cov (%district)	-0.001	-0.034***	-0.026*	-0.034***
	(0.016)	(0.010)	(0.016)	(0.010)
Water network cov (% 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 food expenditures per HH member: alternative calibrations.

Dep. Var.: food spending per cap. (XOF, ln)	(1)	(2)	(3)	(4)
(A) Dist. 2G+ <2km (0/1) × # mob.	0.109**	0.074**	0.084**	0.117***
	(0.044)	(0.033)	(0.034)	(0.031)
(B) Dist. 2G+ <2km (0/1)	-0.865***	-0.518***	-0.422**	-0.289**
	(0.228)	(0.120)	(0.165)	(0.138)
HH controls	No	Yes	Yes	Yes
EA controls	No	No	Yes	Yes
District FEs	No	No	No	Yes
Survey wave FEs	No	No	No	Yes
Observations	56,819	56,817	55,466	55,466
AR F-test (p-val.)	6.04e-10	5.11e-07	0.0133	0.000148
KP Wald F-stat	16.48	41.86	15.74	14.57
KP rank LM-stat	23.20	63.98	20.59	20.10

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

Dep. Var.: Non-food exp. par cap (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline		Alternative calibrations			Urban	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

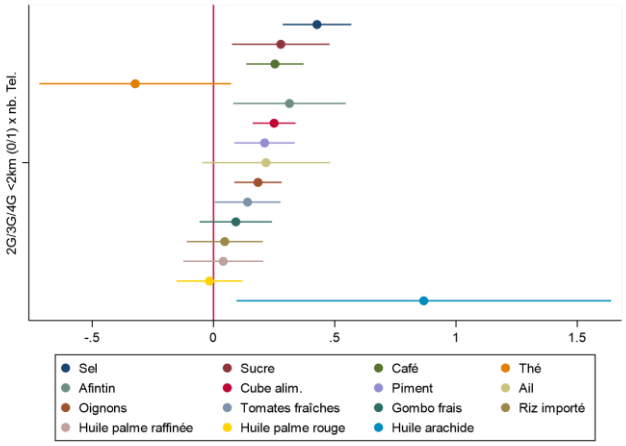
Standard errors in brackets, robust to heteroskedasticity and clustered by EA. * p < 0.1, ** p < 0.05, *** p < 0.01.

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

Dep. Var.: Exp. per cap (XOF, ln)	(2) Food	(3) Non food	(5) Food	(6) Non food	(8) Food	(9) Non food
	All EAs		Urban EAs		Rural EAs	
Dist. 2G+ <2km (0/1) x nb. Tel	0.467**	0.353**	0.125	0.113	0.658*	0.480*
	(0.200)	(0.164)	(0.079)	(0.087)	(0.371)	(0.287)
HH farm sales (XOF, ln)	0.005***	0.004***	0.003	0.004**	0.006***	0.004***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
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	31,006	31,006	5,001	5,001	26,005	26,005
AR F-test (p-val.)	0.000229	0.00515	0.114	0.161	0.000661	0.0128
KP Wald F-stat	10.70	10.54	16.77	16.29	5.019	4.944
KP rank LM-stat	8.497	8.362	11	10.78	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. 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).

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.

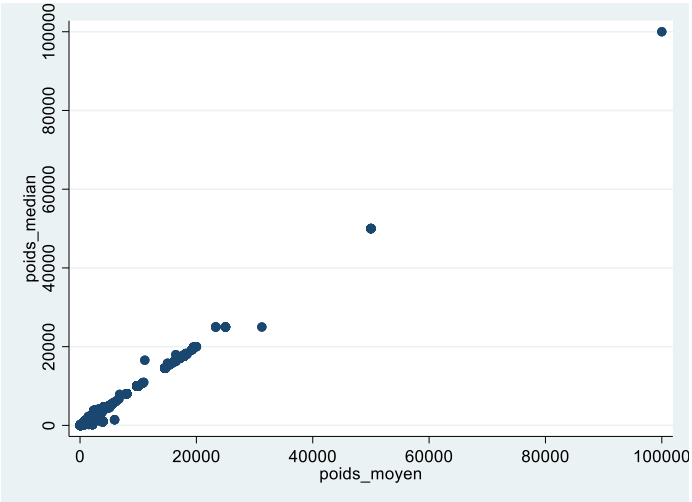
The next step involved merging each of the three databases (Sections 5, 7B, and 16C) with the eight country-specific conversion factor databases. Conversion factors were expressed either in median

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. Estimations based on the second price record

D.1. Network connectivity and food-unit price levels, 2nd stage estimates.

Dep. Var : price record 2	(1)	(2)	(3)	(4)	(5)	(6)
	2nd-stage estimates					
	Non converted price (ln, XOF)			Converted prices (XOF/gram)		
Distance 2G+ (ln, km)	-0.039***			-0.059*		
	(0.011)			(0.034)		
Dist. 2G+ <2km (0/1)		0.118***			0.171*	
		(0.034)			(0.099)	
Dist. 2G+ <5km (0/1)			0.110***			0.171*
			(0.032)			(0.098)
Controls (X_z; $\overline{X_m}$)	Yes	Yes	Yes	Yes	Yes	Yes
District-prod-unit FE	Yes	Yes	Yes	No	No	No
District FE	No	No	No	Yes	Yes	Yes
Prod-unit FE	No	No	No	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	129,738	129,668	129,685	356,605	356,496	356,470
AR F-test (p-val.)	0.00025	0.00027	0.000252	0.0744	0.0740	0.0732
KP Wald F-stat	67.23	47.24	65.34	71.12	56.79	61.63
KP rank LM-stat	47.52	31.70	29.50	40.79	27.20	23.71

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.2 Network connectivity and averaged food price levels, 2nd stage estimates

Dep. var.: $P_{z,j}$ (XOF/gram)	(1)	(2)	(3)	(4)	(5)	(6)
	Averaged product prices†					
	Price record 1			Price record 2		
Distance 2G+ (ln, km)	-0.085**			-0.085**		
	(0.038)			(0.037)		
Distance 2G+ <2km (0/1)		0.253**			0.251**	
		(0.113)			(0.112)	
Distance 2G+ <5km (0/1)			0.248**			0.247**
			(0.109)			(0.107)
Controls (X_z; $\overline{X_m}$)	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	184,057	183,990	183,973	184,055	183,988	183,971
AR F-test (p-val)	0.0176	0.0177	0.0170	0.0169	0.0170	0.0162
KP Wald F-stat	68.71	50.34	61.79	68.71	50.34	61.79
KP rank LM-stat	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. † food-unit prices per gram are transformed into food price per gram by averaging the price per gram of each unit of a given food product.

D.3 Network connectivity and food price convergence, urban versus rural areas, 2nd stage estimates.

Var. dép.: $P_{z,j}$ (XOF/gram)	(1)	(2)	(3)	(4)	(5)	(6)
	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 (X_z; $\overline{X_m}$)	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.

D.4.. Network connectivity and food price dispersion, 2nd stage estimates.

Dep. var: CV_{dju}	(1)	(2)	(3)	(4)
Price record 2:	NC price		C-price	
2G+ coverage (%)	-0.510**	-0.515**	-0.510*	-0.540*
	(0.205)	(0.205)	(0.283)	(0.278)
Ln $P_{d,j}$		0.000***		0.007*
		(0.000)		(0.004)
Controls (X_z; $\overline{X_m}$)	Yes	Yes	Yes	Yes
Region-prod. FE	Yes	Yes	Yes	Yes
Observations	19,399	19,399	24,535	24,535
AR F-test (p-val.)	0.00694	0.00603	0.0598	0.0414
KP Wald F-stat	41.82	41.76	35.38	35.32
KP rank LM-stat	41.51	41.46	35.33	35.28

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.

D.5. Network connectivity, food prices, and the demand channel, 2nd stage estimates.

Dep. var: $P_{z\,i}$ (XOF, ln)	(1)	(2)
Price record 2:	NC prices (ln, XOF)	C prices (XOF/gram)
Network	-0.476**	-1.108*
	(0.192)	(0.647)
Network × EA food spend.	0.029***	0.064*
	(0.010)	(0.033)
EA food spend. (XOF, ln)	-0.020**	0.085
	(0.009)	(0.060)
EA non-food spend. (XOF, ln)	-0.001	-0.124*
	(0.007)	(0.065)
Controls	Yes	Yes
District-prod-unit. FE	Yes	No
District FE	No	Yes
Prod-unit FE	No	Yes
Survey wave FE	Yes	Yes
Observations	129,668	356,494
AR F-test (p-val)	8.31e-05	0.0588
KP Wald F-stat	24.56	29.09
KP rank LM-stat	31.35	26.74

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. Robustness checks

E.1. Augmented network coverage variable

E.1.1. Network connectivity and non-converted food product price, 2nd stage estimates.

Var. Dep: non converted price (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		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.

E.1.2. Network connectivity and converted food product price, 2nd stage estimates.

Var. Dep: converted price (XOF/gram)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		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.

E.1.3. Network connectivity and non-converted food price convergence, urban versus rural areas, 2nd stage estimates.

Var. Dep: non converted price (XOF, ln)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		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	

			(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.

E.1.4. Network connectivity and converted food price convergence, urban versus rural areas, 2nd stage estimates.

Var. Dep: converted price (XOF per gram)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	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.

E.1.5. Network connectivity and quantities of food product consumed, 2nd stage estimates.

Dep var: quantities of consumed commodity / HH member (grams, ln)	(1)	(2)	(3)	(4)
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)
Controls	Yes	Yes	Yes	Yes
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.2. Dealing with spatial anonymization

E.2.1. 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.

E.2.2. 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.

E.2.3. Price level and spatial convergence, 2SLS estimations of Eq. (4) and (5).

Dep. Var (XOF, ln):	(1) Record 1 **IV - bil**	(2) Record 1 **IV - poly**	(3) Record 2 **IV - bil**	(4) Record 2 **IV -poly**	(5) Record 1 **IV - bil**	(6) Record 1 **IV - poly**	(7) Record 2 **IV - bil**	(8) Record 2 **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.3. Reduced-form estimations

E.3.1. Price level and dispersion, reduced-form estimations of Eq. (4)-(6), OLS.

	(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
	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000001)	(0.000)
2020 pop. density (ln)	-	-	0.0022	-	0.0024	
	-	-	(0.0028)	-	(0.0028)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes
District-prod-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.

E.3.2. HH demand for food products, reduced-form estimations of Eq. (7), OLS.

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

E.4.1. 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).

E.4.2. 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.

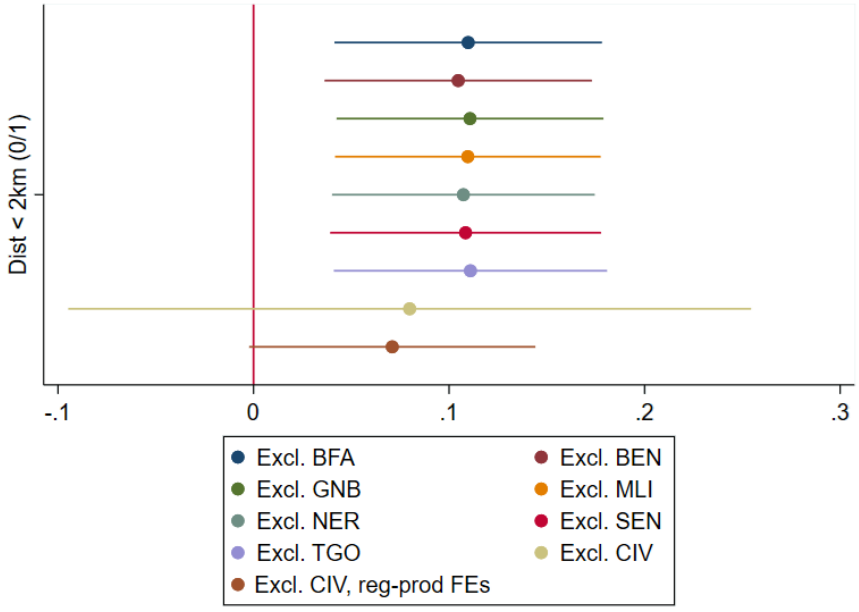
E.5. Additional tests

E.5.1. Digital spillovers and SUTVA violation, 2SLS estimations.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var :	**HH food spend pc (XOF, ln)**			**HH food-prod consumption pc (grams, ln)**		
(A) Dist. 2G+ <2km (0/1) x # mob. cell	0.128***	0.153***	0.140***	0.196***	0.228***	0.233***
	(0.030)	(0.039)	(0.045)	(0.032)	(0.043)	(0.054)
(B) Dist. 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	66.05	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.5.2. Testing the sensitivity to individual country's exclusion



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

F. Literature review

A substantive literature conducted in sub-Saharan Africa and other developing regions highlights the transformative potential of mobile telephony for agricultural markets functioning and household 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), Senegal (Masaki et al., 2020) 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 stronger 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). Studies conducted in Ghana, have found that access to market information through ICTs 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.

This increase in farm or market prices is generally accompanied with a reduction in price dispersion. In Niger, Aker (2010) shows that mobile coverage reduces by 10 to 16% trader price dispersion across grain markets, while Aker and Fafchamps (2015) find that it reduced the spatial dispersion of producer prices for cowpea by 6 percent. 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. Focusing on fishing industry in Kerala, Jensen (2007) also show that mobile phone access led to a strong decline in the coefficient of variation of fish price across markets.

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, as evidenced in Nigeria and Tanzania (Bahia et al., 2021, 2024), or through financial inclusion and improved risk management (Suri et al., 2023). There exists indeed a 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; Bahia et al., 2021, 2024). In Tanzania, Roessler et al. (2021) found that adoption of smartphones by women in Tanzanian households raised per capita consumption by 20%, while Bahia et al (2021) show that 3G network extension led to a 7-11 percentage point increase in HH per capita consumption. Effects of similar magnitude are found in Nigeria (Bahia et al., 2024),

Senegal (Masaki et al., 2020), or Philippines (Labonne & Chase, 2009). Last, a large array of researches 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).