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From phone access to food markets: How mobile connectivity is transforming rural livelihoods in West Africa

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Abstract

We show that mobile connectivity transforms household livelihoods in ways that foster food market integration in WAEMU countries. Using cross-sectional data on nearly 60,000 households and 146 food products traded across 5,000 enumeration areas in eight member states (2018–2019), we combine dyadic and instrumental-variable estimations to identify a demand-led process of spatial food price integration. … /…

Keywords: Connectivity, mobile phone, mobile money, food markets, rural transformation.
JEL : O13, O33, Q11, Q13.

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…/… Dyadic results show that connectivity operates through a spatially layered mechanism: supply-side arbitrage dominates across distant markets and for perishable products, while at local scales price convergence takes the form of a rural–urban catch-up, indicating demand-side adjustments. Household-level analysis supports this mechanism, showing that mobile ownership in covered rural areas increases food purchases and reduces self-consumption, driven by mobile money use and diversification into non-agricultural activities. However, non-adopters in the same locations reduce spending, suggesting negative externalities from higher local prices and limited income gains, and hence heterogeneous welfare effects of connectivity.

1 Introduction

Improving agricultural productivity and strengthening farmers' markets access are central pillars of rural development strategies in low-income countries (de Janvry and Sadoulet, 2022; Suri and Udry, 2022). In sub-Saharan Africa, mobile network roll-out and the massive diffusion of mobile technologies has emerged as a major technological shift (Aker and Mbiti, 2010), with a mixed impact on agricultural outputs but clear benefits for commodity market functioning (Aker and Cariolle, 2023; Abate et al., 2023). A large empirical literature shows that mobile phones and network coverage can foster agricultural market integration and reduce price dispersion through easier spatial arbitrage and stronger farmer bargaining power (Aker, 2010; Nakasone, 2013; Tack and Aker, 2014; Aker and Fafchamps, 2015; Courtois and Subervie, 2015; Soldani et al., 2023; Bergquist et al., 2024). Parallel work documents how mobile technologies may also induce rural transformation dynamics, by easing labor market access and promoting income diversification, facilitating remittances and relaxing other financial constraints, and ultimately, raising household consumption and food security (Jack and Suri, 2014; Nakasone and Torero, 2016; Wantchekon and Riaz, 2019; Masaki et al., 2020; Bahia et al., 2023, 2024; Suri et al., 2023; Batista and Vicente, 2025). Yet these two strands of evidence are rarely studied jointly. In particular, we know much less about how connectivity-induced changes in livelihoods and financial inclusion translate into local food demand and, in turn, reshape food prices and market integration.

This question is especially salient in West Africa, a region characterized by high search and transport costs, fragmented markets, and limited market information (Fafchamps, 2003; Aker, 2010; Aker and Fafchamps, 2015). This paper fills this gap by examining how mobile network connectivity affects food market integration and household welfare across the eight member-states of the West African Economic and Monetary Union (WAEMU). While confirming the role of spatial arbitrage in reducing food price gap for perishable and semi-perishable products at national scale, the analysis highlights the role of rural household food demand in driving local price convergence, for a comprehensive set of traded products. We identify two key mechanisms behind the rise in household food demand: income diversification through off-farm and non-agricultural activities, and financial inclusion via mobile money services. Additionally, we document a negative network externality for households with limited or no mobile access living in covered rural areas. These households likely face higher food prices without commensurate gains in income diversification, underscoring that mobile dividends are unevenly distributed and shaped by general equilibrium effects across food, labor, and financial markets.

To conduct this analysis, we use cross-sectional 2018–19 survey data[1] covering around 59,000 households (HHs) from nearly 5,000 enumeration areas (EAs) and 146 food products traded across the eight WAEMU member states. Our empirical approach relies on dyadic and instrumental variable (IV) estimations to investigate how prices and HH welfare respond to connectivity. The dyadic framework tests whether mutual connectivity between local markets reduces bilateral price gaps (Aker, 2010; Aker and Fafchamps, 2015; Bergquist et al., 2024), while the IV framework identifies the causal effect of network coverage and mobile adoption on food price levels and household livelihoods. Following recent studies (Manacorda and Tesei, 2020; Guriev et al., 2021; Chiplunkar and Goldberg, 2022), network coverage is instrumented by historical exposure to lightning strikes, which raises deployment, repair, and maintenance costs while being plausibly exogenous to current local economic conditions. We nevertheless conduct extensive sensitivity and identification checks, with particular attention to potential violations

[1] From the *Enquêtes Harmonisées sur les Conditions de Vie des Ménages* (EHCVM) jointly conducted by the WAEMU Commission and the World Bank within the Living Standard Measurement Study program.

of the exclusion restriction (Mckenzie, 2024).

Our findings show that mobile connectivity consistently lowers food price dispersion across distant markets, especially for perishable and semi-perishable products, extending to a regional multi-product scale the evidence documented in earlier single-country commodity-specific studies (Jensen, 2007; Aker, 2010; Aker and Fafchamps, 2015; Bergquist et al., 2024). However, dyadic estimations further reveal that supply- and demand-side mechanisms coexist but operate at different spatial scales. At broad national levels, connectivity facilitates long-distance arbitrage and reduces information frictions between far-apart markets, consistent with a supply-led spatial integration mechanism. At finer scales—within regions or districts—price convergence instead takes the form of a rural–urban catch-up, driven by localized demand alignment that plausibly reflects higher household purchasing power and food demand in connected rural areas.

The household-level analysis confirms and sharpens this interpretation. Estimates of household food demand show that acquiring a mobile phone in a covered area increases food spending, particularly in rural communities, aligning with recent evidence on the connectivity–consumption nexus in African countries (Masaki et al., 2020; Bahia et al., 2023, 2024). Mobile connectivity also raises both consumed and purchased quantities of food products, while reducing self-consumption, with stronger effects in rural areas. Crucially, these gains are concentrated among *adopters*: rural and agricultural households with mobile phones in covered EAs substantially increase food spending and market participation. By contrast, non-adopters—and especially non-agricultural households in connected areas—reduce food spending, suggesting a negative externality of coverage driven by higher local prices and lower access to new income opportunities.

Turning to underlying mechanisms, the analysis highlights two complementary channels supporting the demand-side interpretation. First, *income diversification* via enhanced off-farm and non-agricultural employment increases the share of household members engaged in non-farm activities, especially in rural areas, echoing recent findings for Tanzania and Nigeria (Bahia et al., 2023, 2024). Mobile connectivity also promotes non-agricultural enterprise creation and raises margins in unprocessed merchandise sales among rural and agricultural households. These changes help explain why farm households and rural adopters experience larger increases in food demand. Second, *financial inclusion* through mobile money adoption significantly boosts household food expenditures—by around 2% on average and more than 14% in rural areas—again confirming evidence from other sub-Saharan contexts (Suri et al., 2023; Batista and Vicente, 2025). By contrast, internet access is not robustly associated with these mechanisms, suggesting that basic mobile technologies, rather than internet-based services, remain the primary drivers of digital transformation affecting livelihoods and local food demand in this setting.

Taken together, our results show that mobile connectivity fosters food market integration through a spatially layered mechanism: supply-side arbitrage dominates across distant markets, while demand-side adjustments drive convergence at local scales. Connectivity thus acts not only as a coordination technology, but also as a catalyst of rural transformation, enabling many households—especially rural adopters and farm households—to participate more fully in local markets. However, the same general equilibrium forces that raise prices and incomes for some also disadvantage non-adopters and non-agricultural households in connected areas, who face higher food costs without comparable income gains.

Therefore, this paper makes four main contributions to the literature. First, it shifts the focus from the widely studied supply-side determinants of market integration—such as improved spatial allocation of agricultural goods or enhanced bargaining power (Jensen, 2007; Svensson and Yanagizawa, 2009; Aker, 2010; Goyal, 2010; Aker and Fafchamps, 2015; Nakasone, 2013; Tack and Aker, 2014; Courtois and Subervie, 2015; Soldani et al., 2023)—to emphasize demand-side mechanisms driven by rural transformation and their general equilibrium implications. Second, the paper broadens both the geographical and commodity scopes of prior research. While earlier studies typically focus on single countries and a handful of staple crops, our analysis spans eight WAEMU countries and 146 food products, encompassing perishable, semi-perishable, and non-perishable goods. This expanded scope allows us to identify heterogeneous effects of connectivity across product types and spatial scales, thus providing a more comprehensive understanding of how digital infrastructure reshapes food markets. Third, the paper bridges several strands of the digital-for-development literature. It integrates economic outcomes often studied separately—commodity price levels and dispersion (Jensen, 2007; Aker, 2010; Goyal, 2010; Soldani et al., 2023), household food consumption and off-farm labor participation (Masaki et al., 2020; Bahia et al., 2023, 2024), and financial inclusion (Jack and Suri, 2014; Suri et al., 2023)—into a unified empirical framework linking market integration and household welfare through mobile connectivity. Finally, it introduces a methodological improvement by applying standardized conversion factors for non-standard local measurement units. This enables consistent cross-product and cross-country analysis of purchased, consumed, self-consumed food quantities (expressed in grams), and their corresponding local market prices across the region.

Taken together, our analysis suggests that West African economies and rural households are undergoing economic transformations, spurred by the digital transition. However, these changes largely reflect a shift away from agriculture toward more profitable but low-value-added activities, such as informal retailers or artisanal mining, as observed in many African countries (Mensah et al., 2023; Christiaensen and Maertens, 2022). This evidence on the demand-side effects of mobile technologies have important policy implications, as digital infrastructures can trigger general equilibrium effects, with impacts felt across agricultural, financial, labor and nonagricultural markets. Yet, a major downside of mobile connectivity is the exclusion of households with no or limited access to mobile phones. These households do not share in the mobile dividends but still face rising food costs. Closing the usage gap, particularly in rural communities, is therefore essential to ensuring these transformations are inclusive.

The remainder of this article is organized as follows. In Section II, we lay out the background on mobile connectivity and rural livelihoods in West Africa. In Section III, we present the data and estimation framework. Section IV presents and discusses our main results, while Section V analyzes the underlying mechanisms. Section VI presents the robustness analysis. Section VII concludes.

2 Background and literature review

2.1 Agricultural Markets and mobile connectivity in the WAEMU

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, Agriculture, forestry, and fishing contributed 25.7% of GDP, remaining the largest sector in terms of number of workers, though agricultural employment has declined over time. Between 1960 and 2015, 22.5% of the labor force moved out of agriculture, with 19.1% entering services, particularly trade, which requires minimal capital investment (Mensah et al., 2023). This trend is also visible in rural areas, where industry and services have expanded between 2005 and 2019 (Figure 1).

These patterns suggest that rural households seek more stable, diversified, and low-capital livelihoods outside agriculture. Agri-food systems in the WAEMU are indeed undermined by structural constraints, such as low precipitation, poor soil quality, dependence on rain-fed farming, constrained access to agricultural markets and technologies, and weak infrastructure coverage, which contribute to persistent productivity challenges and market variability (Suri and Udry, 2022). Food price dispersion remains high across the region due to search and transaction costs, as producers and retailers face long distances and poor road infrastructure when traveling to markets (Aker, 2010; Tack and Aker, 2014; Aker and Fafchamps, 2015).

In this fragmented market environment, mobile connectivity has the potential to lower trade costs, improving price transparency and trade efficiency (Aker and Mbiti, 2010; Aker and Cariolle, 2023; Bergquist et al., 2024). Since the introduction of mobile phones in the late 1990s, connectivity in the region has expanded rapidly, reaching over 100 mobile subscriptions per 100 residents in most countries by 2022, except in Niger (56 per 100) and Togo (74 per 100). By 2021, over 90% of the population had mobile network coverage (World Bank, 2024). However, despite these advances, a digital divide persists, with rural areas facing lower connectivity and high costs of mobile phone ownership and airtime (Ochoa et al., 2022). Additionally, mobile broadband adoption lags behind feature phones, with only 20% of WAEMU households using mobile broadband in 2018-2019.

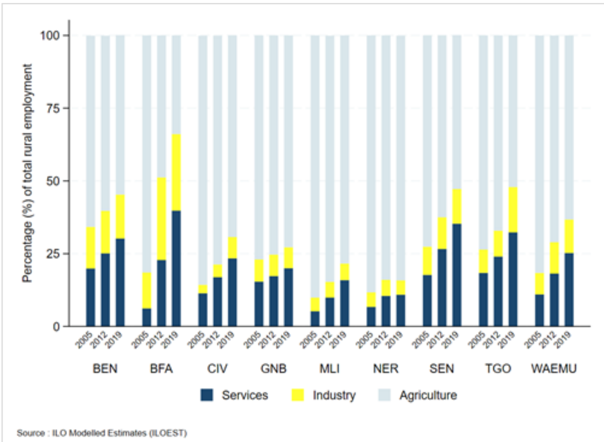

Fig. 1. Evolution of rural employment by sector in WAEMU countries.

Source: Modelled ILO estimates. As modelled estimates, they should be taken with due caution. The drop in employment share in Burkina between 2006 and 2014 is attributed to the 2014 and 2018 surveys being conducted during the dry season (Kruse et al., 2022).

2.2 Mobile phones and rural livelihoods

In the WAEMU region, the rapid expansion of mobile connectivity is transforming agricultural markets and reshaping both on-farm and off-farm activities. On the farm side, mobile phones enhance access to agricultural inputs, market information, and extension services, helping farmers optimize planting schedules, pest control, and input use (Aker, 2011). However, productivity gains have been minimal due to financial and literacy constraints, and the poor design of many digital extension services (Carroll II, 2024; Abate et al., 2023; Aker and Cariolle, 2023). More significantly, mobile connectivity has enhanced farmer bargaining power and traders market outreach, driving price convergence and farm-gate price shifts (Aker and Fafchamps, 2015; Tack and Aker, 2014; Bergquist et al., 2024): for instance, ICT access has increased maize price by 10% in Ghana and 15% in Uganda (Svensson and Yanagizawa, 2009; Courtois and Subervie, 2015), yam prices by 9% in Ghana (Soldani et al., 2023), and reduced grain price dispersion by 10–16% in Niger (Aker, 2010), with similar patterns observed in Peru (Nakasone, 2013) and India

(Jensen, 2007; Goyal, 2010).

While much of the digital agriculture literature attributes agricultural price increases and convergence to supply-side factors (von Cramon-Taubadel and Goodwin, 2021), increased access to inputs and credit, and policy and institutional support, the role of demand-side mechanisms remains overlooked. Yet, in many SSA countries, mobile network expansion spurred increased household food consumption and security (Nakasone and Torero, 2016; Wantchekon and Riaz, 2019; Bahia et al., 2023, 2024), notably by facilitating financial inclusion and supporting consumption through mobile money, helping rural households manage income volatility and seasonal constraints (Jack and Suri, 2014; Lee et al., 2021; Zhang et al., 2022; Zhao et al., 2022; Suri et al., 2023; Batista and Vicente, 2025). Mobile connectivity also eases access to off-farm and non-farm jobs, promoting income diversification. Evidence from India shows that 3G coverage leads to higher share of worker in the agriculture and service industries (Chiplunkar and Goldberg, 2022). Recent evidence from Nigeria, Senegal, and Tanzania links mobile access to higher off-farm employment and a 10 to 20% increase in per capita consumption (Masaki et al., 2020; Bahia et al., 2023, 2024), with effect stronger among rural households (Bahia et al., 2023, 2024).

While mobile connectivity is recognized for enhancing market efficiency and reducing price dispersion through supply-side mechanisms, recent evidence suggests that demand-side factors could play a crucial role in shaping agricultural price dynamics. This perspective enlarges the traditional supply-side narrative and highlights the need for further investigation into how increased consumer demand, facilitated by improved connectivity, affects food market integration.

3 Data and estimation Framework

Our empirical analysis proceeds in two steps. First, we investigate the effect of mobile network connectivity on food-product prices level and dispersion, highlighting the role of food demand in promoting food market integration. Second, we study how mobile phone adoption in connected areas affects household demand for food products and income sources.

3.1 The data

This study is based primarily on cross-sectional data from the Harmonized Survey on Households Living Conditions (EHCVM) 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 1 below. Descriptive statistics of dependent, connectivity and control variables are provided in Appendix A.1 and Online Appendix OA.1.

3.1.1 Dependent variables.

The analysis first focuses on the effect of mobile connectivity on food commodity market prices, observed at the EA level. Then, it shifts at the household level when analyzing the effect of mobile ownership

Table. 1. **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: Data from EHCVM/LSMS.

on household food expenditures, consumption patterns, and income sources. Descriptive statistics of dependent variables are provided in Appendix A.1.1.1.

Food product prices. The price analysis covers 146 food products traded in enumeration areas (EAs) across WAEMU countries. For each product, two independent price observations were collected by surveyors. Since both distributions are overlapping (Figure 2), we rely on the first price record for the main analysis.[2]

Food commodities are often priced in non-standard and heterogeneous units of measurement (e.g., small, medium, or large mounds of chili peppers). To ensure comparability across products and units, we apply product-specific measurement conversion factors to each product–unit combination within each EA.[3] This procedure standardizes all prices into XOF per gram.[4] After conversion, spatial (EA-level) and temporal deflators are applied to account for price-level differences across space and time. The resulting standardized prices are winsorized at the 99th percentile and subsequently log-transformed for the analysis.

Household food consumption. We investigate the effect of digitalization on the demand for commodities, using i) deflated food spending per household member, and ii) quantities of food product (self-)consumed and purchased per household member, as dependent variables. The measurement of quantities (self-)consumed and purchased was made possible using the commodity measurement-unit conversion factors for non-standard units of measurement in grams.

3.1.2 Mobile connectivity variables.

We consider the 2G (voice/SMS) network as the primary digital infrastructure in WAEMU's largely rural food markets.[5] We nevertheless extend the infrastructural scope to 3G and 4G networks, measuring connectivity via (i) spatial proximity to nearest 2G, 3G or 4G (2G+) cell towers at the EA level, and

[2] Results using the second price record are robust and reported in a previous version of this paper; they are available upon request. The list of the most frequently traded product–unit combinations across EAs is provided in Online Appendix OA.1.1.2.

[3] Online Appendix OA.4 details the computation and application of these conversion factors.

[4] In an earlier version of this paper, we alternatively used, for each commodity, the log-transformed non-converted price of the most commonly traded product–unit pair in the WAEMU region. District–product–unit fixed effects (FEs) were included to control for local and inherent price heterogeneity. Results based on this non-converted specification are available upon request.

[5] Mensah (2023) provides global evidence showing that mobile coverage raises local economic activity, with 2G effects concentrated in developing countries and particularly salient where fixed-line infrastructure was scarce—making basic telephony a key driver of growth in settings like ours. Hjort and Poulsen (2019) put in evidence a positive effect of broadband access on African jobs, but their analysis focuses on formal firms mostly located in urban centers.

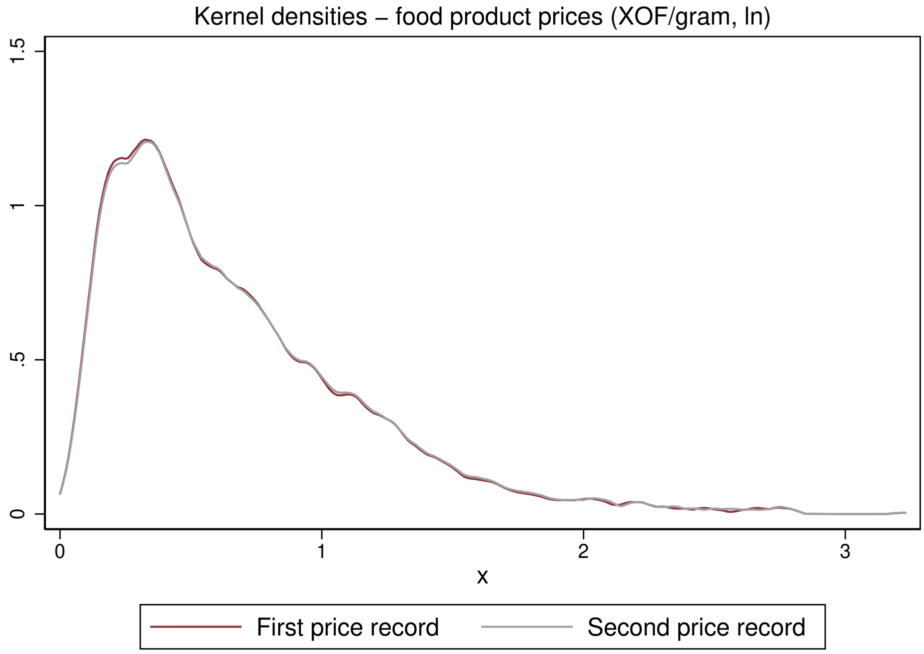

Fig. 2. **Distribution of food product prices (XOF/gram, ln), Kernel densities, records 1 & 2.**

(ii) mobile adoption in connected areas at the household level. Internet access is analyzed separately in Section 6. Given low internet penetration in rural West Africa, we expect weaker direct effects of 3G+ on food markets and rural development relative to 2G-based technologies (Abate et al., 2023; Aker and Cariolle, 2023). Descriptive statistics for mobile connectivity variables are reported in Appendix A.1.2.2.

Mobile network coverage. We use geo-coded data on the spatial deployment of 2G+ cell towers from the OpenCellID project[6], and use the following two main network access variables:

- The logarithmic distance (in km) from the EA centroid to the nearest 2G+ tower.[7]
- A dummy variable equal to 1 if the EA centroid is within 2 km of the tower, 0 otherwise. For the sake of results' interpretation simplicity, we use this variable as main interest variable.[8]

Figure 3 displays the spatial dispersion of mobile network connectivity across EAs. On average, households are located in EAs located 14 km from the nearest 2G+ tower, and 51% of these HHs are located within a 2km radius from the closest tower. Complementarily, we study the long term and quality effects of connectivity by respectively using i) the years since the cell tower's arrival and ii) the number of mobile operators providing good reception, within 2km of the EA centroid.

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

[7] 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.

[8] But estimated relationships across the analysis are robust to the use of the continuous distance variable. We additionally use a dummy variable equal to 1 if the EA centroid is within 5km (or 12km) of the tower, 0 otherwise.

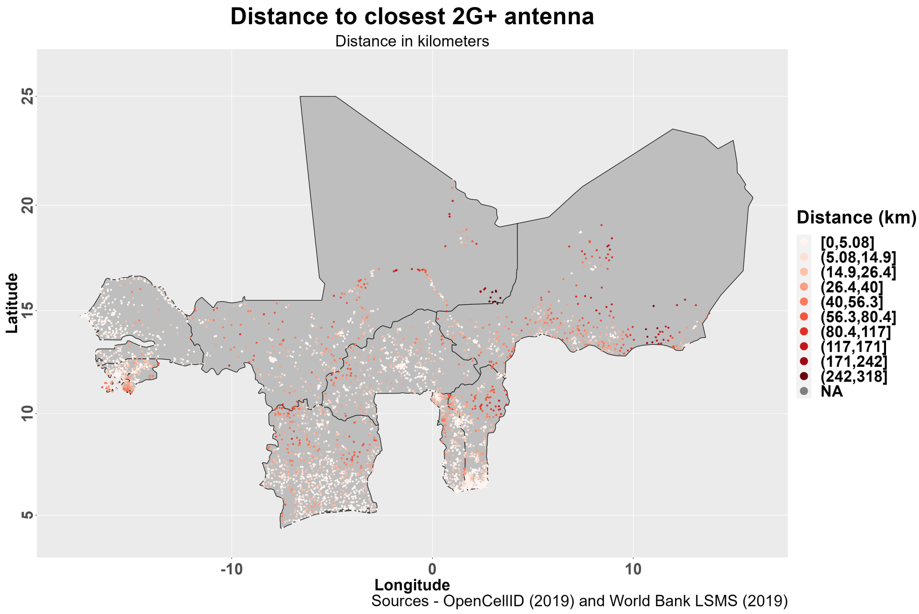

Fig. 3. **Mobile network access in the WAEMU, 2018-2019.**

Mobile adoption. Household-level digital connectivity is measured by mobile phone adoption in connected areas, which is a variable equal to the number of mobile phones in the household covered by the mobile network. Mobile connectivity is our main focus since access to calling and SMS features of basic mobile phones, rather than internet (30% of household had access to internet inside or outside their home, 13% in rural areas), is found to play a pivotal role in agricultural and rural development (Aker and Mbiti, 2010; Abate et al., 2023; Aker and Cariolle, 2023).

Using the number of mobile phones rather than a simple ownership dummy offers greater variation, as 90% of surveyed households already own at least one device. It also captures the degree of mobile adoption within the household, reflecting both intra-household communication needs and occupational diversity: many members combine on- and off-farm activities or work in dispersed locations, which often requires multiple devices (Van den Broeck and Kilic, 2019).

Figure 4 illustrates the strong link between mobile network proximity and adoption intensity. Areas located within 2 km of a 2G+ tower display a greater share of households owning a mobile phone and average number of devices per household, the later being markedly higher than in less connected areas (left-hand side graph). Moreover, the number of phones per household strongly decreases with network distance (right-hand side graph), suggesting that better signal quality not only increases access but also deepens usage, as households expand their digital assets once reliable connectivity is available.

3.1.3 Control variables.

We control for household characteristics and a number of determinants of local agricultural and economic development. These control variables and their associated descriptive statistics are detailed in Online Appendix OA.1.2.1.

EA-level controls. In price-level estimations, we control for local economic development by the density of nighttime lights, for contemporaneous and average rainfall over the 2015-2019 period, for demographic

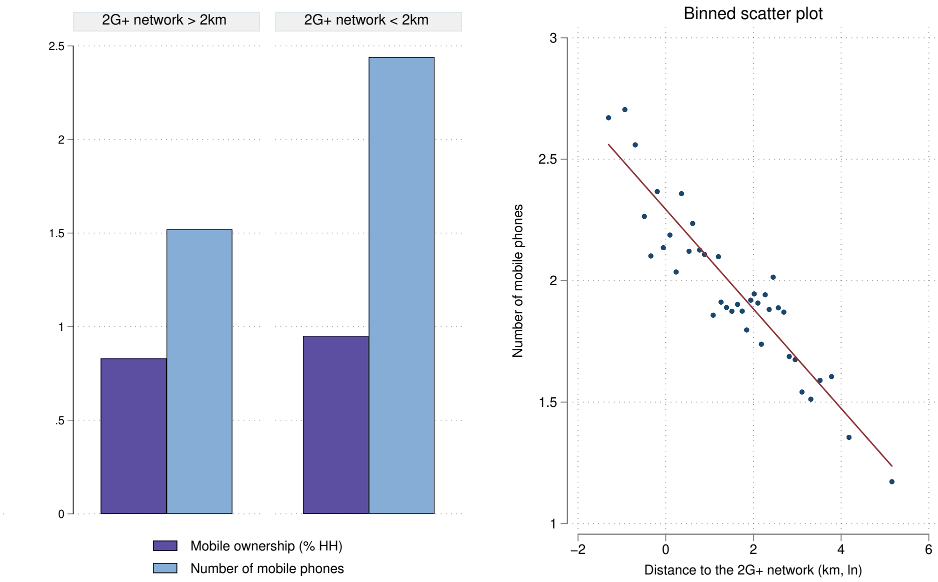

Fig. 4. Household mobile ownership and network access.

Right-hand side graph is a binned scatter plot, controlling for the EA distance to the closest urban center (km, ln).

characteristics of the EA (i.e., population density in 2015 and total EA population), and for the EA's distance from the nearest urban center[9].

Household-level controls. We control for the characteristics of the head of household, i.e., gender, age, level of education and literacy, and marital status (monogamous or polygamous). We also control for household size, access to finance, access to internet, housing characteristics, standard of living (through ownership of various assets, such as a television, fridge, etc.), access to electricity and sanitation infrastructure, experience of idiosyncratic and covariant shocks of various kinds (health, income, climate, etc.), and total area of cultivated plots per adult equivalent.

3.2 Empirical framework

Our empirical strategy proceeds from market-level integration patterns to the household behaviors that can generate them. We first study spatial price dispersion, testing whether connectivity reduces price gaps over long distances—consistent with improved spatial arbitrage—and whether effects vary with product perishability. We then examine *price levels* to assess whether convergence takes the form of rural–urban catch-up, i.e., rising prices in connected rural markets relative to nearby urban benchmarks, which is suggestive of stronger local demand. Finally, we use household data to test this mechanism directly by estimating how connectivity and mobile adoption affect food purchases, consumption, and income diversification. Together, these analyses trace a pathway from mobile coverage to food-market integration and rural transformation.

[9] Alternatively an rural/urban dummy when estimating interaction terms.

3.2.1 Conceptual framework and testable hypotheses

Mobile connectivity can affect food markets through two main channels — a *supply-side integration* channel and a *demand-side transformation* channel — which operate at different spatial and product scales.

Supply-side mechanisms. Information and communication technologies reduce information search, coordination, and transaction costs in agricultural markets (Nakasone, 2013; Aker and Fafchamps, 2015; Bergquist et al., 2024). Producers and traders can better compare prices, time shipments, and minimize spoilage losses, leading to tighter spatial price linkages and smaller price gaps. These effects are expected to be strongest across *distant markets*, where coordination frictions and transport costs are high, and for *perishable and semi-perishable products*, whose storability is low and for which intertemporal arbitrage is limited (Barrett and Li, 2002; Aker and Fafchamps, 2015; von Cramon-Taubadel and Goodwin, 2021).

H1 (Supply-side integration): Connectivity reduces price dispersion, and the effect is stronger across distant markets.

Demand-side mechanisms. Mobile connectivity also transforms rural livelihoods by improving access to information, credit, and remittances, expanding off-farm activities and access to mobile-money services in low-price isolated markets (Nakasone and Torero, 2016; Batista and Vicente, 2025; Suri et al., 2023). These effects raise local purchasing power and market participation (Wantchekon and Riaz, 2019; Masaki et al., 2020; Bahia et al., 2023, 2024). Unlike supply-led integration, this channel operates primarily within local markets, shifting local demand upward rather than lowering trade frictions between distant markets. Hence, mobile networks may increase prices in connected rural markets and reduces rural–urban price gaps, without necessarily affecting trade costs.

H2 (Demand-side transformation): Connectivity raises food prices in connected rural markets, narrowing local rural–urban gaps.

Spatial scale and mechanism identification. When identifying variation is large (e.g., across region/district or long routes), spatial arbitrage dominates and the connectivity effect strengthens with bilateral distance. When it is local (e.g., within region/district), information frictions are softer and price convergence mainly reflects demand-led rural–urban catch-up centered on nearby hubs.

H3 (Scale differentiation): Supply-driven effects dominate over long distances; demand-driven effects play locally.

Product heterogeneity. The storability of food products traded in the WAEMU determine how connectivity maps into prices across space.[10] Because perishables and semi-perishables have limited storability, they are subject to *spatial* (rather than intertemporal) arbitrage by farmers and traders (Barrett and Li, 2002; Aker and Fafchamps, 2015; von Cramon-Taubadel and Goodwin, 2021). By contrast, non-perishables are highly storable and cheaper to move; their responses to connectivity are less distance-sensitive.

H4 (Product scope of spatial arbitrage): Spatial arbitrage operates for perishable and semi-perishable goods; non-perishables price gap exhibits weak sensitivity to market distance.

[10] Online Appendixes OA.1.1.2 and OA.1.1.1 categorize the 15 most trade food products according to their perishability.

3.2.2 Baseline model

We estimate the impact of mobile connectivity on outcomes measured at either the enumeration area (EA) or household level, using the following general specification:

$$Y_{z/h,j} = \alpha, CON_{z/h} + \Gamma X_{z/h} + \sum_{f \in \mathcal{F}} \eta_f + \mu_t + \varepsilon_{z/h,j}, \tag{1}$$

where $Y_{z/h,j}$ denotes the outcome of interest—such as the logarithm of the price (XOF per gram) of commodity–unit pair j traded within EA z, or household-level h outcomes such as food spending per capita. The vector $X_{z/h}$ includes relevant control variables, while μ_t captures survey-wave fixed effects. The term $\sum_{f \in \mathcal{F}} \eta_f$ represents the set of spatial and product fixed effects included in the specification, to account for unobserved heterogeneity across markets, commodities, and measurement units. Specifically, $\mathcal{F} \in \{a, p, a \times p\}$ indicates that we include either additive administrative unit and product-unit fixed effects—for example, district (d) and product-unit pair (j)—or their interacted form (e.g., district-by-product-unit fixed effects), depending on the specification. Standard errors are robust to heteroskedasticity and clustering.

3.2.3 Dyadic estimations.

We first test whether mobile connectivity reduces food price dispersion using a dyadic framework adapted from literature (Aker, 2010; Aker and Fafchamps, 2015; Bergquist et al., 2024). Letting $Y_{ijzz'}$ be the log of the absolute price difference of product j between EAs z and z' from country i, we estimate:

$$Y_{ijzz'} = \delta \, CON_{izz'} + \Delta X_{izz'} + \mu_{ij} + \mu_z + \mu_{z'} + \varepsilon_{izz'j}, \tag{2}$$

where $CON_{izz'}$ equals one if EAs z and z' lie together within 2 km of a 2G+ tower.[11] $X_{izz'}$ is a set of controls including the bilateral geographic distance between EAs, the absolute difference in local nighttime light intensity (as a proxy for local economic activity), and an indicator for whether both EAs belong to the same district. All models include EA_z and EA'_z fixed effects (μ_z and $\mu_{z'}$), as well as country $\times$ product FEs (μ_{ij}), to absorb unobserved local and product characteristics. Additional calibrations include paired region ($r_{zz'}$) or district ($d_{zz'}$) FEs to exploit different levels of identifying variation. Standard errors are thrree-way clustered by EA_z and EA'_z and their respective district pair $d_{zz'}$.

This specification thus tests whether markets that share network coverage exhibit smaller food price gaps. Because both the dependent and key independent variables are defined as EA differences and the model combines a large set of FEs, this design mitigates reverse causality and omitted variable bias linked to unobserved local traits.

3.2.4 Instrumental variable estimations.

To address potential endogeneity between connectivity and economic outcomes in market-level or household-level analysis, we instrument mobile coverage in 2018-2019 with historic daily lightning strike density, averaged over 1998-2013, a structural cost shifter that raises cell-tower construction, protection, and maintenance costs and affects mobile operator's roll-out plan over the long run (Andersen et al., 2012;

[11] Dyadic variables were paired between EAs from the same country due to computational constraint, pairing only EAs that have been surveyed during the same wave.

Manacorda and Tesei, 2020; Guriev et al., 2021; Chiplunkar and Goldberg, 2022). Following Guriev et al. (2021) and Chiplunkar and Goldberg (2022), we weight lightning density by population density to reflect that the deterrent effect of lightning on coverage is weaker in densely populated areas.[12]

The instrument is defined as:

$$Z_z = Lightning\_density_z^{1998-2013} \times \frac{1}{1 + popdens_z^{2015}}, \tag{3}$$

and the first stage equation is:

$$CON_z = \gamma\, Z_z + \Gamma X_z + \mu_t + \mu_d + \varepsilon_z. \tag{4}$$

Summary statistics and a regional map of lightning strikes are provided in Appendix A.1.3.3 and A.1.3.2. OLS estimates of Equation 4 shown in Figure 5 confirm that lightning exposure predicts weaker coverage (greater tower distance, later rollout, fewer captured signals), and its effect remains robust after controlling for contemporaneous and four-year average rainfall, other EA-level controls, supporting its orthogonality to contemporaneous meteorological and economic conditions, as already shown in the US context by Andersen et al. (2012) (See detailed estimates in Online Appendix OA.2.1.1).[13]

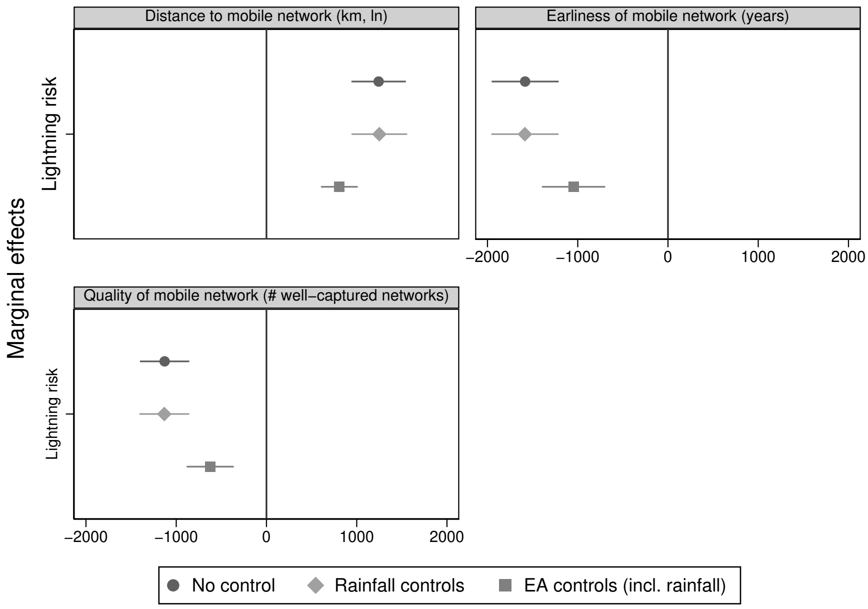

Fig. 5. Network coverage and lightning risk (Z_z), OLS estimates, Eq(3).

Note: 4,764 EAs. Estimates of equation (3) with district and survey wave FEs are reported. GMM-robust standard errors, clustered by district. Controls include contemporaneous and 2015-2019 average rainfall, nighttime light density, population density, EA population size, and distance to the closest urban center.

[12] Lightning data come from the LIS 0.1° Very High-Resolution Gridded Lightning Climatology (Albrecht et al., 2016). See Online Appendix OA.3 for details. Baseline estimates using an alternative measure of lightning exposure based the annual frequency of lightning strikes are reported in Online Appendix OA.2.2.1 and confirm our results.

[13] We expect this daily exposure to lightning strikes to reflect permanent exposure to lightning activity rather than seasonal exposure, presumably higher during the rainy season. Moreover, if historical exposure to lightning captured rainfall-driven determinants of network roll-out, the instrument should be *positively* correlated with local development, and hence, network coverage. Instead, our first stage shows that *higher* lightning risk robustly leads to *lower* network coverage and quality, while reduced form estimations highlight a negative effect of the instrument on price and household welfare.

Household-level analysis. The household specification follows from the local rural–urban price catch-up: coverage raises local prices, implying heterogeneous welfare effects among *adopters* and *non-adopters* in a context of higher food costs. A key implication is that a standalone "coverage effect" under SUTVA and homogeneous-effects assumptions, as commonly done in the connectivity literature, is not a welfare-relevant estimand because it mixes winners and losers from connectivity.[14]

We therefore estimate the effect of *coverage conditional on adoption* and include a coverage main effect to capture price externalities on non-users. To keep CON_z identified in the main specification, we include *district* (rather than EA) fixed effects:

$$Y_{mj} = \beta_1\,(CON_z \times AD_h) + \beta_2\,AD_h + \beta_3\,CON_z + \Gamma' X_h + \mu_d + \mu_t + \mu_j + \varepsilon_{hj} \tag{5}$$

where Y_{hj} is food spending (ln) or product j quantity (ln). The endogenous regressors are CON_z and $CON_z \times AD_h$; β_1 is the treatment-on-the-treated for adopters in covered EAs, while β_3 captures coverage externalities on non-adopters. Standard errors are clustered at the EA level.

We therefore augment the estimation framework including this additional first-stage equation:

$$(CON_z \times AD_h) = \pi_1\,(Z_z \times AD_h) + \pi_2\,AD_h + \Pi' X_h + \mu_d + \mu_t + \mu_j + \upsilon_{hj},$$

As a tighter control for local heterogeneity, we also replace μ_d with *EA* fixed effects (μ_z), which mechanically drops CON_z as time-invariant within EA and focuses identification on β_1. Across specifications, we control for household characteristics, wealth, education, and infrastructure access (Appendix A.1). Therefore, we assume that *instrumented network coverage determines adoption, conditional on household-level observables*. Pre-rollout placebo checks show that the lightning-based instrument does not predict adoption before coverage arrives, supporting this conditional exogeneity assumption[15]; nonetheless, we interpret the resulting estimates with due caution.

4 Main results

We start by showing, through a dyadic analysis of price gaps, that mobile connectivity significantly reduces spatial price dispersion across WAEMU member states for a broad basket of food staples. Results in the first sub-section suggest that connectivity contributes to food markets integration through both long-distance spatial arbitrage and local rural-urban catch-up. The next sub-sections explore how these patterns manifest in higher household market consumption and relaxed liquidity constraints.

4.1 Mobile network connectivity and food product market prices

4.1.1 Food price dispersion: dyadic estimations

We first examine whether mobile phone coverage reduces food price dispersion between markets. We estimate Equation 2, regressing absolute log price differences between enumeration areas (EAs) on indicators

[14] These spillovers imply that standard SUTVA and homogeneous-treatment assumptions are unlikely to hold in connectivity studies that treat network coverage as a single, uniform treatment. When coverage raises local prices and affects labor, input, or financial market functioning for both users and non-users, a single "effect of coverage" conflates direct impacts on adopters with general-equilibrium effects on non-adopters. Similar issues arise for large economic stimuli more broadly: for example, Egger et al. (2022) document sizable spillovers of a cash-transfer program on non-recipient households and firms in rural Kenya, implying large local multipliers and highlighting the importance of general-equilibrium effects when interpreting welfare impacts.

[15] See Section 6.3 and Appendix Table A.3.2.2

of mutual connectivity, controlling for bilateral distance, nightlight gaps, and EA-level and district-dyads unobservables. Results are shown in Table 2.

Table. 2. Mobile network coverage and price dispersion in the WAEMU: Dyadic estimations.

Dep. var.: $\ln\lvert\Delta p_{zz'}\rvert$	(1)	(2)	(3)	(4)	(5)
Within variation :		**Country**		**Region**	**District**
$CON_{zz'}$	-0.0239***	-0.0092***	-0.0168**	-0.0126***	-0.0134**
	(0.0019)	(0.0009)	(0.0051)	(.0034)	(0.0029)
$CON_{zz'}\times$ Bilateral dist.			-0.0049***	0.0008	0.0013***
			(0.0009)	(0.0006)	(0.0005)
Bilateral dist. (km, ln)		0.0207***	0.0230***	0.0058***	0.0071***
		(0.0006)	(0.0007)	(0.0006)	(0.0013)
$\lvert\Delta$ Nightlights$\rvert$		0.0001***	0.0001***	0.0002***	0.0002***
		(0.00003)	(0.00003)	(0.00002)	(0.00002)
Same district (0/1)		-0.0324***	-0.0349***	-0.0187***	–
		(0.0047)	(0.0046)	(0.0023)	–
Paired admin. unit zz' FE	No	No	No	$Region_{zz'}$	$District_{zz'}$
Observations	20,201,454	19,154,484	19,154,484	19,154,484	19,154,484
EAs	4,916	4,709	4,709	4,709	4,709
R^2 (adj.)	0.440	0.444	0.445	0.448	0.450

Notes: Robust standard errors in parentheses, clustered by origin z and destination z' enumeration areas (EAs) and their paired district zz'. The dependent variable is the log absolute price difference between EA_z and $EA_{z'}$. First price record used. $CON_{zz'}$ is a dummy variable indicating that EA z and z' are both located within a 2km-distance from the closest 2G+ cell-tower. All regressions include EA_z, $EA_{z'}$ FEs, and country × product FEs. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Columns (1)–(2) show that mutually connected EAs display significantly smaller price gaps—about 1% lower on average, after controlling for bilateral distance and local development differences. Although modest in magnitude, this convergence effect spans a heterogeneous basket of 146 food products. In column (3), the negative interaction between connectivity and distance supports that coverage fosters spatial arbitrage between within-country distant markets, consistent with reduced trading and search costs.

Columns (4)–(5) progressively narrow the identifying variation by adding region- and district-dyad fixed effects. As the spatial scale tightens, the distance gradient weakens and eventually reverses, while the main connectivity effect attenuates. These patterns suggest that cross-regional convergence mainly reflects supply-driven integration, whereas within-region or district pair convergence is more consistent with local adjustments, possible driven by demand-side mechanisms.

To further separate supply- and demand-led mechanisms, we next disaggregate products by perishability. We restrict the analysis to the 15 most frequently traded goods, and group them into three categories—perishable, semi-perishable, and non-perishable—based on storability and transport sensitivity.[16] Supply-driven effects should dominate for perishables and strengthen with distance, while demand-driven effects should emerge for all goods but play at the local level.

Table 3 reports dyadic estimates of Equation 2 across product groups—perishable, semi-perishable, and non-perishable—and at different spatial scales. First, the convergence effect of connectivity is consistently negative and statistically significant at *national* and *sub-national* spatial scales, but its magnitude declines as the scale narrows (rows (A1, B1, C1) × columns (1, 3, 5)). This is particularly striking for *perishable* and *semi-perishable products*. For the former, connectivity effects remain positive and significant but fall by roughly two-thirds when restricting to within-district pairs variation (row (A1) × columns (1, 3, 5)); while for the latter, the connectivity effect vanishes (row (B1) × columns (1, 3, 5)). By contrast,

[16] See Appendix Table OA.1.1.1 for classification.

non-perishable products' price gap estimates seem less sensitive to spatial scales (row (C1) × columns (1, 3, 5)).

Second, how distance moderates price gaps depends on perishability and scale, revealing a joint role for supply- and demand-side mechanisms in convergence. For *perishables* at the *national scale*, gaps grow with distance and connectivity softens that distance penalty (rows (A2, A3) × column (2))—a standard supply-side arbitrage pattern. At *sub-national scales* this moderating role weakens (row (A2) × columns (4, 6)). For *semi-perishables*, connectivity narrows gaps at *national* and *regional scales* (row (B1) × columns (1, 3)), and (standalone) distance still widens gaps everywhere (row (B3)). However, within regions and districts the interaction turns positive (row (B2) × columns (4, 6)): connectivity compresses gaps among nearby markets (rows (B1, B2)× columns (4, 6)), but it amplifies the gap-widening role of distance as markets get farther apart (rows (B2, B3) × columns (4, 6)). Read together, the distance term and its (now positive) interaction imply localized price-convergence clusters of connected areas—consistent with stronger local demand rather than long-haul arbitrage. For *non-perishables*, the interaction is generally insignificant across scales (row (C2)), which is plausible given their higher storability and the basic nature of these goods (sugar, salt, rice, ...), whose demand is less elastic to income changes.

4.1.2 Food price levels: IV estimations

Having shown that mobile coverage reduces spatial price dispersion, we now examine its effect on price levels, controlling for district-level unobserved heterogeneity, to identify which markets experience convergence locally, i.e. within districts. Table 4 reports instrumental-variable (IV–2SLS) estimates of Equations 1–4, with different fixed-effects calibrations and clustering levels. First-stage statistics confirm instrument strength and relevance. Specification with alternative network distance radius (5km, 12km), reduced-form estimates, and OLS estimates are provided in Online Appendix A.2.1.1. Baseline results indicate that a 1% reduction in the distance to the nearest 2G+ tower increases food prices by about 1% in average (Columns (1) and (3)), while EAs within 2 km of a tower record prices 3–4% higher than unconnected ones. These magnitudes are consistent with evidence on specific commodities from Svensson and Yanagizawa (2009), Goyal (2010), and Aker and Fafchamps (2015), among others, and remain robust to alternative fixed effects and clustering specifications.[17]

Table 5 examines rural–urban heterogeneity. Columns (1)–(4) show that the price effect of connectivity is essentially a rural phenomenon: in rural EAs, being within 2km of a 2G+ tower increases local food prices by about 5–6%, whereas the corresponding coefficients for urban EAs are small, negative, and statistically negligible. Columns (3)–(4) split the sample by whether local prices are below (price gap < 0) or above (price gap > 0) the average urban price in the same district. The estimated effects indicate that price increases are concentrated in underpriced rural markets, while price decreases occur in overpriced urban markets, echoing recent evidence on food market adjustments in Uganda (Bergquist et al., 2024). However, the signs of the coefficients in underpriced urban areas and overpriced rural areas do not point to systematic spatial arbitrage or a clear rebalancing of supply across locations.

To properly assess whether the catch-up effect of connectivity on rural prices effectively translates into reduced price gaps, we estimate in columns (5) to (8) the same model using the absolute deviation of a

[17] As estimates are unaffected by the inclusion of two-way clustering (column 6), subsequent regressions use one-way clustering for computational efficiency.

Table. 3. **Mobile network coverage and price dispersion, by product perishability: Dyadic estimations.**

Dep. var.: $\ln\lvert\Delta p_{zz'}\rvert$	(1)	(2)	(3)	(4)	(5)	(6)
Within variability	**Country**		**Region**		**District**	
	Panel A: Perishable products					
(A1) $CON_{zz'}$	−0.0138***	0.0241**	−0.0113***	−0.0241***	−0.0053***	−0.0022
	(0.0026)	(0.0118)	(0.0023)	(0.0088)	(0.0019)	(0.0077)
(A2) $CON_{zz'} \times \ln \text{Dist}_{zz'}$		−0.0071***		0.0024		−0.0006
		(0.0021)		(0.0016)		(0.0014)
(A3) $\ln \text{Dist}_{zz'}$	0.0315***	0.0345***	0.0119***	0.0105***	0.0080***	0.0084***
	(0.0014)	(0.0017)	(0.0016)	(0.0016)	(0.0027)	(0.0026)
$\lvert\Delta$ Nightlights$\rvert$	0.0003***	0.0003***	0.0004***	0.0004***	0.0003***	0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same district (0/1)	−0.0153**	−0.0191**	−0.0257***	−0.0254***		
	(0.0078)	(0.0076)	(0.0050)	(0.0049)		
Constant	0.1426***	0.1250***	0.2450***	0.2529***	0.2657***	0.2633***
	(0.0077)	(0.0090)	(0.0085)	(0.0083)	(0.0144)	(0.0142)
Observations	1,737,072	1,737,072	1,737,072	1,737,072	1,736,764	1,736,764
R^2 (adj.)	0.383	0.383	0.404	0.404	0.427	0.427
	Panel B: Semi-perishable products					
(B1) $CON_{zz'}$	−0.0101***	0.0691***	−0.0074***	−0.0297***	−0.0019	−0.0324***
	(0.0028)	(0.0140)	(0.0022)	(0.0098)	(0.0020)	(0.0093)
(B2) $CON_{zz'} \times \ln \text{Dist}_{zz'}$		−0.0151***		0.0042**		0.0058***
		(0.0025)		(0.0017)		(0.0017)
(B3) $\ln \text{Dist}_{zz'}$	0.0339***	0.0418***	0.0073***	0.0045**	0.0095***	0.0048*
	(0.0022)	(0.0023)	(0.0017)	(0.0019)	(0.0027)	(0.0027)
$\lvert\Delta$ Nightlights$\rvert$	−0.0003***	−0.0002***	0.0001**	0.0001**	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Same district (0/1)	−0.0292***	−0.0358***	−0.0175***	−0.0169***		
	(0.0103)	(0.0101)	(0.0047)	(0.0048)		
Constant	0.1450***	0.1001***	0.2742***	0.2894***	0.2612***	0.2867***
	(0.0118)	(0.0122)	(0.0090)	(0.0100)	(0.0140)	(0.0139)
Observations	1,477,602	1,477,602	1,477,602	1,477,602	1,476,924	1,476,924
R^2 (adj.)	0.542	0.542	0.570	0.570	0.591	0.591
	Panel C: Non-perishable products					
(C1) $CON_{zz'}$	−0.0048***	0.0019	−0.0037***	0.0003	−0.0033***	−0.0052
	(0.0011)	(0.0050)	(0.0010)	(0.0037)	(0.0010)	(0.0040)
(C2) $CON_{zz'} \times \ln \text{Dist}_{zz'}$		−0.0013		−0.0007		0.0004
		(0.0009)		(0.0007)		(0.0008)
(C3) $\ln \text{Dist}_{zz'}$	0.0102***	0.0108***	0.0020***	0.0025***	0.0034***	0.0032***
	(0.0006)	(0.0007)	(0.0006)	(0.0005)	(0.0011)	(0.0008)
$\lvert\Delta$ Nightlights$\rvert$	0.0001*	0.0001*	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Same district (0/1)	−0.0156***	−0.0162***	−0.0075***	−0.0075***		
	(0.0040)	(0.0039)	(0.0018)	(0.0018)		
Constant	0.0711***	0.0680***	0.1146***	0.1121***	0.1068***	0.1083***
	(0.0036)	(0.0037)	(0.0034)	(0.0030)	(0.0060)	(0.0047)
Observations	3,309,354	3,309,354	3,309,354	3,309,354	3,309,232	3,309,232
R^2 (adj.)	0.506	0.506	0.514	0.514	0.520	0.520
Admin. unit zz' FEs	No	No	$Region_{zz'}$	$Region_{zz'}$	$District_{zz'}$	$District_{zz'}$

Notes: Robust standard errors in parentheses, clustered by origin EA_z and destination $EA_{z'}$ and their paired district zz'. Dependent variable is the log absolute price difference between EA_z and $EA_{z'}$. $CON_{zz'}$ is a dummy variable indicating both EAs are within 2 km of a 2G+ tower. 15 most traded products in the WAEMU are classified according to their perishability as follows: **Perishable** – fresh tomato, fresh okra, fresh onion, whole chicken, fresh pepper, beef; **Semi-perishable** – red palm oil, peanut butter, potato, afintin/soumbala; **Non-perishable** – salt, sugar, tomato paste, imported long-grain/broken rice, peanut oil. All regressions include EA_z, $EA_{z'}$, and product×country fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table. 4. **Impact of 2G+ network proximity on food product prices : IV estimations.**

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.: Food price (XOF, ln)	**Second-stage estimates**					
CON_z (km, ln)	−0.0099**		−0.0139***			
	(0.0039)		(0.0043)			
CON_z (<2km, 0/1)		0.0282**		0.0402***	0.0356**	0.0402***
		(0.0112)		(0.0125)	(0.0139)	(0.0148)
Dist. urb. center (km, ln)	0.0092***	0.0091***	0.3190***	0.0084***	0.0070***	0.0084***
	(0.0016)	(0.0016)	(0.0040)	(0.0015)	(0.0017)	(0.0018)
Contemp. rainfall			−0.0232***	−0.0240***	−0.0254***	−0.0240***
			(0.0036)	(0.0036)	(0.0036)	(0.0040)
Past rainfall (Av. 2015–2019)			0.0306***	0.0336***	0.0328***	0.0336***
			(0.0055)	(0.0055)	(0.0057)	(0.0070)
Nighttime light			−0.0004***	−0.0004***	−0.0002**	−0.0004***
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
Pop. density			−0.0000***	−0.0000***	−0.0000*	−0.0000*
			(0.0000)	(0.0000)	(0.0000)	(0.0000)
EA pop. size (ln)			−0.0039***	−0.0039***	−0.0032***	−0.0039***
			(0.0005)	(0.0005)	(0.0006)	(0.0007)
	First-stage estimates					
IV	865.33***	−304.85***	788.57***	−273.19***	−280.28***	−273.19***
	(19.44)	(7.39)	(19.05)	(7.17)	(5.97)	(35.70)
Dist. to urb. center (km, ln)	0.3636***	−0.1254***	0.3190***	−0.1075***	−0.1079***	−0.1075***
	(0.0042)	(0.0013)	(0.0040)	(0.0013)	(0.0009)	(0.0047)
Contemp. rainfall			0.0681***	−0.0025	−0.0214***	−0.0025
			(0.0116)	(0.0045)	(0.0048)	(0.0194)
Past rainfall (Av. 2015–2019)			−0.2296***	0.0051	0.0158*	0.0051
			(0.0361)	(0.0122)	(0.0095)	(0.0470)
Nighttime light			−0.0114***	0.0046***	0.0049***	0.0046***
			(0.0005)	(0.0002)	(0.0001)	(0.0005)
Pop. density			0.0000***	−0.0000***	−0.0000***	−0.0000***
			(0.0000)	(0.0000)	(0.0000)	(0.0000)
EA pop. size (ln)			−0.0484***	0.0165***	0.0177***	0.0165***
			(0.0024)	(0.0009)	(0.0007)	(0.0040)
District × product × unit FEs	Yes	Yes	Yes	Yes	No	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	No	No	No	No	Yes	No
Product × unit FEs	No	No	No	No	Yes	No
Clustering	One-way					Two-way
Obs.	357,234	357,124	346,377	346,267	356,546	346,267
AR F-stat	0.0114	0.0114	0.00132	0.00132	0.0100	0.00686
KP Wald F-stat	1982	1701	1714	1453	2201	58.56
LM-weak	507.6	420.3	466.5	384.5	648.7	25.42

Notes: GMM-robust standard errors in parentheses, one-way clustered at district × product level. Two-way clustering in column (6) adds EA-level clustering. CON_z refers to 2G+ network raw/dummy distance variables. Prices are log-transformed food-product prices, deflated by EA-level spatial deflators and temporal deflators, and winsorized at 99%. Reported first-stage statistics robust to heteroskedasticity and clustering. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

product's price from the district-level average urban price.[18] Results in columns (5) to (6) show that, once attenuating the influence of extreme deviation through winsorization, mobile network coverage in rural areas is associated with a statistically significant reduction in the absolute price gap. Splitting the sample between underpriced and overpriced rural areas, the estimates in columns (7)–(8) reveal heterogeneous adjustments by gap sign: the decline in the absolute price gap is concentrated in underpriced rural markets, while overpriced locations exhibit no significant convergence. Overall, this evidence indicates that network connectivity induces a rural–urban catch-up in food prices, primarily through upward adjustments in underpriced rural areas, consistent with the hypothesis of demand-side pressure operating in these markets. The next section further tests this mechanism by investigating the combined effect of mobile network coverage and mobile adoption on household food demand.

Table. 5. Network connectivity and local food price outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Price level (XOF, ln)				$\|Price\ dev.\|$(%)			
						99%-winsorized deviations		
Price gap:			< 0	> 0			< 0	> 0
CON_z (0/1)	−0.014 (0.020)	0.056*** (0.013)	0.036*** (0.012)	0.012 (0.017)	−0.037 (0.024)	−0.050*** (0.017)	−0.081*** (0.015)	0.037 (0.038)
$CON_z \times$ Dist.	0.021*** (0.007)							
$CON_z \times$ Urban		−0.073*** (0.017)	−0.028 (0.015)	−0.066*** (0.021)	−0.002 (0.027)	0.033* (0.019)	0.081*** (0.017)	−0.095* (0.052)
Dist. urb. (km, ln)	−0.006 (0.004)							
Urban (0/1)		0.005 (0.010)	0.033*** (0.009)	−0.056*** (0.012)	−0.103*** (0.014)	−0.100*** (0.011)	−0.069*** (0.010)	−0.189*** (0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	346,267	346,267	238,246	106,017	317,513	317,513	238,246	77,263
KP Wald F-stat	674.9	733.3	530.9	307	698.3	698.3	530.9	302.6
LM-weak	541	566.1	397.5	314.1	542.7	542.7	397.5	293.1

Notes: Robust standard errors in parentheses, clustered at the district × product level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. All regressions include district × product × unit and survey-wave fixed effects. Second-stage estimates reported. First-stage and control variable estimates not reported. CON_z refers to the 2km-distance 2G+ network dummy variable. **Rural EA with negative gaps:** 2,366 EAs, 124 products. **Rural EA with positive gaps:** 2,386 EAs, 127 products. **Urban EAs with negative gaps:** 2,072 EAs, 143 products. **Urban EAs with positive gaps:** 1,993 EAs, 140 products. Prices are log-transformed food-product prices, deflated by EA-level spatial deflators and temporal deflators and winsorized at 99%. *Dist. urb.* is the distance (km, ln) to the closest urban center. *Price gap* is the difference between a product's price and the average price in urban areas within the same district. $|Price\ dev.|$ is the absolute deviation between a product's price and the average price in urban areas within the same district, expressed as a share of district's urban average price. CON_z refers to 2G+ network proximity variables.

4.2 Mobile connectivity and household food demand

Evidence of a catch-up effect of network connectivity on food prices in rural areas has potential welfare and distributional implications for rural households in connected places: while adopters may benefit from digital services and income diversification, non-adopters may face higher living costs without equal access to income opportunities. We therefore move from market-level price effects of connectivity to the demand effects of connectivity conditional on mobile adoption, emphasizing a network externality on poorly digitalized households.

[18] Measured as $\left|\frac{P_{z,j}-\bar{P}_{d,j}}{\bar{\bar{P}}_{d,j}}\right|$, with $P_{z,j}$ the price of product j observed in EA z, and $\bar{P_{d,j}}$ the urban average price of product j in district d.

4.2.1 Food spending in connected households and network externalities

Table 6 reports IV estimates of the effect of mobile coverage and phone ownership on household food spending per capita, as specified in Equation (5). Across all specifications, the endogenous regressors are the coverage dummy CON_z[19] and the interaction $CON_z \times AD_h$, which captures the effect of coverage conditional on mobile phone ownership by the household.

All households (Panel A). Specifications in Panel A move from a parsimonious specification without controls (col. 1) to richer models with EA-level controls and finer fixed effects (cols. 2–4). Across estimations, first-stage statistics support the IV validity, the interaction term is large, positive, and significant, while the stand-alone coverage term CON_z is negative and significant whenever included.[20] Interpreted jointly, coverage raises food spending for mobile owners but lowers it for non-owners in covered EAs, highlighting a negative externality on non-adopters. The implied marginal effect of adoption in covered EAs ranges from about 5% to 12% per additional phone in the specifications with controls (cols. 2–4).[21] By contrast, the marginal effect of coverage at the sample mean (of two phones) is close to zero or mildly negative (cols. 2–3), indicating that the aggregate effect of coverage on food spending largely reflects offsetting gains for adopters and losses for non-adopters.

Urban vs. rural households (Panel B). In urban areas, estimated effects are small and mostly insignificant. The coverage main effect and the interaction are both non-significant, and the implied marginal effect of adoption in covered EAs is negligible. This suggests limited pass-through of coverage and adoption to food spending in cities, where markets are better integrated. By contrast, rural areas display much sharper heterogeneity. Coverage has a large negative effect for rural non-adopters ($\hat{\beta}_{CON_z} \simeq -0.48$), while the interaction $CON_z \times AD_h$ is also large but positive. The implied marginal effect of adoption in covered rural EAs is about 22–25% per additional phone (cols. 2-4), and the net effect of coverage at average ownership levels (two devices) turns positive (around 17%) (col. 2). Thus, mobile coverage reduces food spending for rural households without phones but substantially raises it for rural adopters.

Agricultural vs. non-agricultural households (Panel C). Panel C shows that this distributional pattern is tightly linked to livelihood. Among agricultural households, the marginal effect of adoption in covered EAs is strong and positive—around 13% per phone in the district-FE specification (col. 1) and close to 20% with EA fixed effects (col. 3)—and the marginal effect of coverage at two phones is also positive (col. 1). Farm households with mobile phones are therefore clear winners from mobile network expansion. Among non-agricultural households, by contrast, coverage has a negative and significant main effect (col. 2), driven by the negative externality on non-adopters, and the marginal effect of adoption in covered EAs is close to zero. The negative externality of coverage is thus concentrated among non-agricultural rural households, who are on average more connected and richer but net buyers

[19] To ease results interpretation, we report estimates using the binary connectivity variable, equal to one when the EA is located within a 2km radius of the closest 2G+ cell tower.

[20] Result confirmed in robustness checks reported in Appendix Table A.3.1.2 showing estimated effects with higher signal quality and earlier roll–out within the same EA. Placebo tests (Online Appendix Table A.3.2.2) also show the IV predicts phone adoption in connected areas only *after* network arrival, supporting the identification assumption for this series of estimations.

[21] These magnitudes echo recent micro–evidence from Senegal (+14% in HH consumption) (Masaki et al., 2020), Nigeria (+10%) (Bahia et al., 2024), and Tanzania (+7%) (Bahia et al., 2023).

of food (Appendix Table OA.1.3.1), and therefore do not benefit to the same extent from the income and market-access gains that connectivity generates for farm households.

Taken together with the rural–urban price convergence previously documented, these results point to a distributional wedge: coverage induces a rural price catch-up and raises food spending for adopters—especially among rural and agricultural households—while non-adopters in connected areas face higher living costs and lower food spending.

4.2.2 Quantities of product consumed, purchased and self-consumed.

We next assess whether the increase in household food spending documented above reflects higher quantities consumed or simply higher prices. Table 7 reports 2SLS estimates using the same specification, with dependent variables measuring the logarithm of the quantity (in grams) of food products consumed, purchased, and self-consumed per household member. First-stage statistics remain above standard thresholds –including for rural sub-samples–, indicating that weak-instrument concerns are low. Results confirm previous results, showing that mobile adoption in connected areas significantly raises both consumed and purchased quantities, while reducing self-consumed quantities. For the full sample, one additional mobile phone within connected households increases quantities of food consumed and purchased by about 6-7% – which is within the same range as previously-evidenced food spending increase – while reducing self-consumption by roughly 2%.

These patterns are, again, stronger for rural households, where the estimated semi-elasticities reach 24–33% for total and purchased quantities, respectively, and the drop in self-consumption exceeds 10%. In urban EAs, the effects of mobile connectivity are smaller for quantities consumed and purchased, but not significant for self consumption, consistent with lower reliance on self-production and easier market access in these areas. Together with the results on food spending, these findings suggest that mobile connectivity promotes a shift from subsistence toward market-based consumption patterns, consistent with a price catch-up led by rural transformation.

Table. 6. **Network connectivity and household (HH) food spending per capita**

	(1)	(2)	(3)	(4)
	Panel A: All HHs			
CON_z	-0.1984**	-0.2409**	-0.2966***	
	(0.0888)	(0.1018)	(0.1079)	
$CON_z \times AD_h$	0.1177***	0.1138***	0.1106***	0.2096***
	(0.0296)	(0.0302)	(0.0326)	(0.0403)
AD_h	-0.1087***	-0.0615***	-0.0595***	-0.0912***
	(0.0195)	(0.0260)	(0.0216)	(0.0259)
Controls	No	HH & EA	HH & EA	HH
Admin unit FE	District	District	Region	EA
Observations	54,898	54,898	54,898	54,898
AR F-stat	0.000249	4.09e-04	3.89e-04	3.19e-08
KP Wald F-stat	56.32	54.15	40.48	95.42
LM-weak	66.38	64.89	49.30	61.94
	Panel B: Urban vs. rural HHs			
	Urban	Rural	Urban	Rural
CON_z	-0.1304	-0.4834**		
	(0.1510)	(0.2166)		
$CON_z \times AD_h$	0.0191	0.3226**	0.1094**	0.3741***
	(0.0456)	(0.1413)	(0.0478)	(0.1437)
AD_h	-0.0179	-0.1037**	-0.0881*	-0.1200**
	(0.0432)	(0.0493)	(0.0456)	(0.0495)
Controls	HH & EA	HH & EA	HH	HH
Admin unit FE	District	District	EA	EA
Observations	22,079	32,819	23,135	33,099
AR F-stat	0.693	4.09e-05	0.0336	5.82e-05
KP Wald F-stat	26.79	5.947	47.46	12.20
LM-weak	12.74	9.707	21.64	9.801
	Panel C: Agricultural vs. non-agr. HHs			
	Agr.	Non-agr.	Agr.	Non-agr.
CON_z	-0.2646*	-0.4007*		
	(0.1473)	(0.1878)		
$CON_z \times AD_h$	0.2021***	0.0482	0.2934***	0.0778
	(0.0722)	(0.0659)	(0.1139)	(0.0693)
AD_h	-0.0711**	-0.0240	-0.0963**	-0.0656
	(0.0309)	(0.0612)	(0.0484)	(0.0656)
Controls	HH & EA	HH & EA	HH	HH
Admin unit FE	District	District	EA	EA
Observations	33,349	21,549	33,574	21,784
AR F-stat	0.0312	0.0153	6.97e-04	0.267
KP Wald F-stat	21.57	42.75	13.62	49.61
LM-weak	21.25	42.75	13.62	49.61

Notes: The dependent variable is deflated food spending per household member (XOF, log). Standard errors in parentheses, robust to heteroskedasticity and clustered at the EA level. CON_z is the 2-km coverage dummy (2G+); AD_h is the number of mobile phones in the household. Endogenous terms are instrumented using population-weighted lightning strike density and its interaction with AD_h. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table. 7. **Mobile connectivity and quantity of commodities (self-)consumed and purchased per household (HH) member, 2SLS second-stage estimates.**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.:	Quantity of commodity per HH member (grams, ln):								
	All EAs			Urban EAs			Rural EAs		
	C	P	SC	C	P	SC	C	P	SC
$CON_z \times AD_h$ (A)	0.198***	0.290***	−0.072**	0.235***	0.303***	−0.029	0.397***	0.601***	−0.183*
	(0.031)	(0.037)	(0.029)	(0.071)	(0.075)	(0.039)	(0.110)	(0.158)	(0.093)
AD_h (B)	−0.136***	−0.222***	0.052***	−0.213***	−0.282***	0.027	−0.156***	−0.270***	0.080**
	(0.024)	(0.029)	(0.022)	(0.069)	(0.072)	(0.037)	(0.046)	(0.071)	(0.039)
$\delta Y/\delta AD_h$	0,062***	0,068***	-0,020***	0,022***	0,021***	-0,002	0,241***	0,331***	-0,103*
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	941,659	731,57	1,143,284	479,068	414,111	554,037	462,163	337,035	588,709
KP Wald F-stat	99.88	99.38	105.6	41.59	39.83	43.73	21.97	20.58	13.90
KP rank LM-stat	66.57	73.88	69.69	20.39	19.04	20.32	16.73	16.95	11.15

Notes: Standard errors in brackets, robust to heteroskedasticity and clustered by EA. Control estimates are not reported. AD_h is the number of mobile phones owned by the HH. CON_z refers to the 2-km dummy variable (2G+ network). Estimations additionally include the diversity of consumed food products (number of distinct products consumed by the HH) as control variable, but remain robust to its exclusion. Reported first-stage statistics are robust to heteroskedasticity and clustering. C, P, and SC denote consumed, purchased, and self-consumed, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Mechanisms

In this section, we unpack mechanisms explaining demand-led rural-urban food price catch-up, by exploring two complementary channels: (i) shifts in income diversification into off- or non-farm activities, and (ii) financial inclusion through mobile money adoption.

5.1 Income diversification

Income diversification away from agriculture is a key channel through which mobile connectivity can affect food prices and rural welfare. Improved access to digital communication and information lowers transaction and search costs, expands labor opportunities beyond farming, and facilitates small-scale entrepreneurship (Aker and Cariolle, 2023). To test this channel, we estimate Equation 5 on household members' workforce allocation and non-agricultural activities.

Table 8 reports IV estimates of the effects of mobile coverage and phone ownership on labor outcomes. In all three panels, the interaction term is positive and statistically significant, with larger coefficients in rural areas, indicating that mobile ownership in covered EAs raises household members' engagement in on-farm and, more strongly, in off-farm income-generating activities. A similar effect is recorded on the number of non-agricultural enterprises operated by the household. These results extend at the regional scale recent evidence of Bahia et al. (2023, 2024) for Nigeria and Tanzania, who document similar increases in labor force participation in off- or non-farm work associated with network expansion.

Importantly, standalone network effect (CON_z) on off-farm and non-farm activities is again negative and significant, confirming that coverage without mobile ownership tends to reduce income-earning opportunities for households with few or no phones. This result mirrors the previous results on food spending, where coverage raised consumption for adopters but lowered it for non-adopters, and together they are consistent with a negative externality of mobile coverage on non-users: connectivity enables income diversification and higher food consumption primarily for covered adopters.

Figure 6 and Appendix table A.2.4.2 explore the income diversification mechanism further by analyzing household non-agricultural revenues. Mobile connectivity is found to improve margins in unprocessed merchandise sales, particularly among rural and agricultural households. For these groups, the margins in non-transformed merchandise sales rise by nearly 0.3–0.4 standard deviations. In parallel, we also observe a significant reduction in revenues from processed merchandise among the same rural and agricultural households, pointing to a shift away from value-added or capital-intensive processing toward simpler but more profitable forms of trading and non-farm labor.

Table. 8. Network connectivity and labor outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	# On-farm activities / HH member				# Off-farm activities / HH member				# non-agricultural enterprises			
	All HHs		Urban	Rural	All HHs		Urban	Rural	All HHs		Urban	Rural
$CON_z \times AD_h$	0.0728***	0.0646***	0.0497**	0.1761***	0.0889***	0.0893***	0.0637**	0.2888***	0.1096**	0.1120**	0.0699	0.2746*
	(0.0153)	(0.0137)	(0.0210)	(0.0673)	(0.0189)	(0.0199)	(0.0325)	(0.1104)	(0.0434)	(0.0449)	(0.1072)	(0.1489)
AD_h	-0.0428***	-0.0362***	-0.0442**	-0.0562**	-0.0450***	-0.0474***	-0.0430	-0.0912**	0.0214	0.0120	0.0097	-0.0256
	(0.0100)	(0.0090)	(0.0201)	(0.0226)	(0.0126)	(0.0132)	(0.0308)	(0.0378)	(0.0280)	(0.0294)	(0.1010)	(0.0517)
CON_z	-0.0802				-0.2164***				-0.3477**			
	(0.0568)				(0.0547)				(0.1382)			
Controls	EA & HH	HH	HH	HH	EA & HH	HH	HH	HH	EA & HH	HH	HH	HH
Admin. unit FEs	District	EA	EA	EA	District	EA	EA	EA	District	EA	EA	EA
Observations	54,895	56,231	23,132	33,099	56,231	56,231	23,132	33,099	54,898	56,234	23,135	33,099
R-squared	0.154	0.104	0.152	-0.066	0.175	0.138	0.240	-0.438	0.199	0.177	0.215	0.133
AR F-stat	9.02e-06	3.13e-06	0.0305	9.28e-05	6.75e-07	2.64e-06	0.0533	4.74e-06	0.00655	0.0110	0.509	0.0283
KP Wald F-stat	19.40	101.3	47.19	11.61	55.90	101.3	47.19	11.61	19.38	101.2	47.21	11.55
LM-weak	25.91	65.73	21.48	9.360	64.65	65.73	21.48	9.360	25.89	65.61	21.48	9.315

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered by EA. Estimations include survey wave and EA FEs, except in columns (1), (5) and (9) which include district Control estimates are not reported. AD_h is the number of mobile phones in the household; CON_z is the 2-km coverage dummy (2G+). In columns (9) to (12), estimations add the number of years since the first non-agricultural enterprise creation in the HH to the set of baseline controls. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

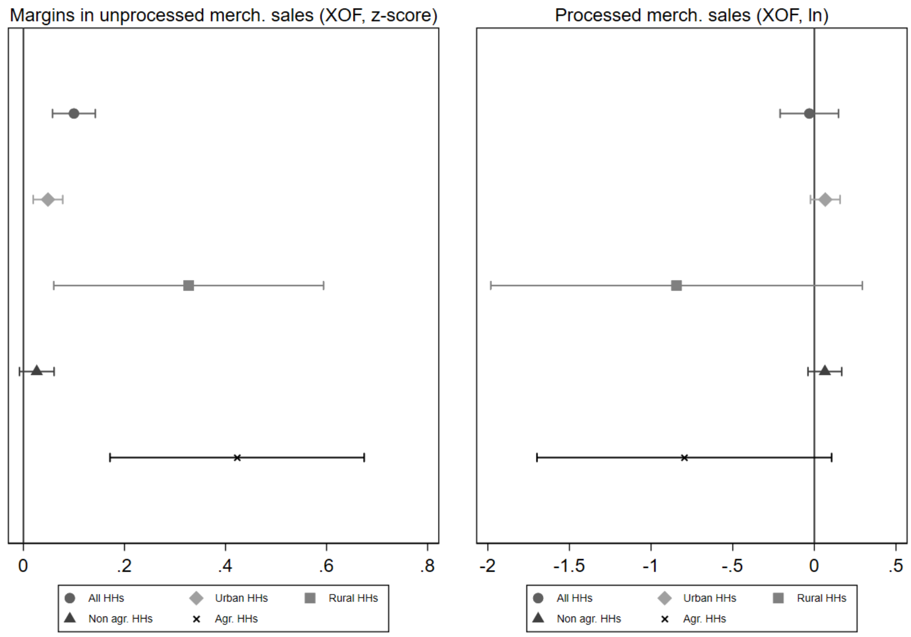

Fig. 6. **Mobile connectivity and non-agricultural incomes, marginal effects, IV estimations. Note: Marginal effects of mobile ownership in connected areas reported.**

5.2 Mobile money

Financial inclusion through mobile money (MM) services is another plausible channel for the impact of mobile connectivity on rural household's food demand (Lee et al., 2021; Zhang et al., 2022; Zhao et al., 2022; Suri et al., 2023; Batista and Vicente, 2025). MM facilitates money transfers within and across borders, enabling rural households to purchase food, invest in agriculture, or start small businesses. In the WAEMU, MM is the primary tool for financial inclusion, with 34% of surveyed households owning at least one MM account (Appendix Table A.2.3.1).

To assess the prominence of this channel, we include a MM ownership dummy and its interaction with mobile phone adoption in Equation 5. Results in Table 9 indicate that MM adoption partly mediates the effect of mobile connectivity on food demand. In fact, MM ownership increases food spending by 1.8% overall (column 3), an average effect driven by a 14%-increase in rural areas (column 5). Mobile money likewise increases consumed quantities in rural areas (column 8) but is associated with lower consumed quantities in urban areas (column 7). A plausible explanation is net transfers flowing from urban to rural relatives via mobile money, leading to consumption deprivation for urban household members (Lee et al., 2021; Batista and Vicente, 2025). These findings suggest that MM diffusion contributes to rural food price convergence and reduced price dispersion through its role in supporting food consumption and promoting local development.

Table. 9. **Mobile money and household food consumption**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Food spending / HH memb. (XOF, ln)					Food consum. / HH memb. (gr, ln)		
	All HHs			Urban	Rural	All HHs	Urban	Rural
Dist. 2G+ <2km (0/1) × nb. tel	0.128***		0.098***	0.094**	0.301*	0.162***	0.198***	0.329***
	(0.029)		(0.029)	(0.048)	(0.182)	(0.029)	(0.069)	(0.096)
Dist. 2G+ <2km (0/1) × MM		0.202***	0.165**	0.054	0.305**	0.114***	0.063	0.279**
		(0.068)	(0.068)	(0.104)	(0.134)	(0.044)	(0.060)	(0.118)
MM account owner (0/1)		−0.170***	−0.147***	−0.091	−0.161**	-0.208**	-0.195***	-0.246***
		(0.039)	(0.039)	(0.092)	(0.064)	(0.029)	(0.054)	(0.051)
# Mobile phones	−0.073***	0.015***	−0.052***	−0.074	−0.093**	-0.106***	-0.175***	-0.121***
	(0.020)	(0.003)	(0.019)	(0.046)	(0.047)	(0.022)	(0.067)	(0.040)
HH controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prod-unit FEs	–	–	–	–	–	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56,211	56,211	56,211	23,116	33,095	941,495	478,920	462,147
KP Wald F-stat	103.9	108.7	51.20	24.49	5.813	49.49	21.87	10.69
LM-weak	67.66	69.33	66.82	21.94	9.316	64.75	20.89	15.97

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered by EA. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Second stage estimats reported. Control variable estimates not reported. Control variables additionally include non-food spending per household member in columns (1) to (5), and food diversity in columns (6) to (8), but results are robust to their exclusion.

6 Additional evidence and robustness checks

6.1 Long term and quality effects

Until now, our analysis did not consider heterogeneity in the timing of network expansion. To capture the long term effects of mobile network exposure on food markets, we replace the 2 km-proximity dummy in equation (1) with a variable measuring the number of years since a cell tower was deployed within 2 km of the EA centroid. This allows us to assess the influence of prolonged network exposure on food-product price and food spending patterns. Results in Appendix A.3.1.1 confirm baseline estimations, that is, an overall increase in food prices (+1%) (Column 1), observed in rural areas (+1.6%) (Column 6), leading to a reduction in the rural-urban price gap (-1.2%) in under-priced rural areas (Column 8). Household food spending are also found to respond positively to the length of exposure to the mobile network, as shown in Appendix A.3.1.2 (Column 1).

Moreover, recognizing limitations in our proximity-based connectivity measure—such as its inability to account for varying network quality, due for instance to geographic conditions, maintenance issues, or limited infrastructure sharing—we augment our analysis combining LSMS data on the number of well-captured networks in each EA with OCI data on cell-tower location. Estimates confirm the robustness of baseline results, the role of network quality, and the instrument validity, showing that greater network quality strengthens the impact of mobile connectivity on food market price catch-up (Appendix A.3.1.1, Columns 2-5, 7 and 10-11) and household food demand (Appendix A.3.1.2, Columns 2-5).[22]

6.2 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 trading platforms, social media, or digital agricultural extension advice (Abate et al., 2023). We therefore re-estimate equation (2) by interacting the network connectivity variable with the internet adoption dummy, which was ultimately included as a standalone control variable, and controlling for mobile ownership.

Estimates are reported in Appendix Table A.2.2.1. First-stage statistics support instrument validity, but the impact of internet access is more moderate and less robust across urban and rural sub-samples than the effects of mobile phone access in general. This likely reflects the higher cost of internet use and the lower absorptive capacity for internet-based technologies in (rural) WAEMU communities. Consistently, Appendix Table A.2 (column 2) shows that the positive effect of connectivity on local prices becomes stronger when we extend the network radius to 12 km—the theoretical range of 2G voice/SMS but beyond the effective reach of most 3G+ internet services. Taken together, these results suggest that the impacts and mechanisms documented in the paper are driven primarily by basic mobile connectivity rather than by internet access.

6.3 Sensitivity and identification tests

6.3.1 Heterogeneity in lightning exposure and instrument validity tests

Appendix Table A.3.2.1 assesses the robustness of the identification strategy by accounting for potential nonlinearities and geographic heterogeneity in the IV effect on network access. In columns (1)–(2), we

[22] Results are also robust to the use of the raw LSMS data on the raw number of well-captured signals as instrumented connectivity variable. They can be provided upon request.

augment the specification with the squared term of the instrument to allow for a non-linear relationship between lightning exposure and coverage, considering that the marginal deterrent effect of lightning may change with exposure intensity. In columns (3)–(4), we interact the instrument with altitude, while controlling for altitude itself, to test whether the impact of lightning on network expansion is stronger in topographically exposed locations (e.g., higher elevations).

In both specifications, the additional terms are significant in the first stage, and the excluded-instrument statistics remain strong, confirming that the instrument variants retain predictive power for network distance. Most importantly, Hansen–J tests fail to reject the null of joint instrument validity, supporting that the identifying variation captured by lightning exposure—and its geography-driven amplification—does not operate through alternative channels.

In Online Appendix Table OA.2.2.1, we provide additional evidence on the robustness of estimated relationships, using an alternative indicator of lightning strike density, measured as the annual frequency of lightning strikes. Results show that, evidence of a rural-urban catch-up effect of network connectivity on food price are consistent and robust with this alternative, though-weaker (but still strong), version of the instrument.

6.3.2 Placebo tests

Appendix Table A.3.2.2 then presents a placebo test distinguishing between households that owned a mobile phone before local network rollout ("early adopters") and those that acquired one afterward ("late adopters"). If the estimated effects of connectivity on food spending are causal, they should arise only among late adopters only, i.e., households whose effective communication capacity changed with network arrival.

Results support this expectation. Among early adopters, the interaction term between network connectivity and mobile ownership is small, statistically insignificant, and accompanied by weak first-stage relevance (KP Wald < 1), indicating no systematic relationship between network distance and household food spending prior to coverage. By contrast, the coefficient for late adopters is negative and significant ($p < 0.01$) with strong first-stage statistics, consistent with our main findings: households experience higher food spending per member when connectivity improves and they adopt mobiles after rollout. The results remain robust after including household control variables, reinforcing the interpretation that household-level effects are driven by network-induced adoption rather than by selection on observables.

6.3.3 Sensitivity checks

First, we check whether baseline estimates are affected by spatial anonymization, which could lead to bias when using geo-coded survey data in rural contexts. Spatially anonymized datasets such as the LSMS may indeed lead to measurement errors due to privacy protection methods, consisting of randomly offsetting true EA coordinates by 0 to 2 km in urban areas, and 2 to 5 km in rural areas, with an additional small percentage of EAs offset 1 to 10 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 OA.2.4, and report baseline estimations in associated Table OA.2.4.1, to build our instrumental variable and other geo-coded control variables. Results remain robust to this check.

Second, we assess the robustness of the estimated impact of network connectivity on food price levels (Equation 1) to the exclusion of each 8 WAEMU member state in turn. Figure OA.2.5.1 plots the resulting coefficients when countries are sequentially dropped from the sample. The positive effect of mobile coverage on food prices remains remarkably stable in both magnitude and significance across all sub-samples, indicating that the results are not driven by any single country. When Côte d'Ivoire is excluded—by far the largest market in the sample, accounting for about 22% of all enumeration areas—the estimate becomes less precisely estimated but remains positive and statistically significant at the 10% level, and the instrument retains strong predictive power (KP Wald $F = 31.7$). Overall, we conclude that the main price-level results are robust to this conservative country-by-country sensitivity check.

7 Conclusion

This paper investigates how mobile connectivity reshapes food markets and household livelihoods across the WAEMU region. Using spatially rich price and household data, we show that mobile network expansion reduces food price dispersion, but through distinct mechanisms across spatial scales and product types. At broader distances, particularly for perishable and semi-perishable goods, convergence reflects the standard supply-side channel: improved information flows and arbitrage across distant markets. At finer, local scales—within regions and districts—convergence instead reflects localized demand alignment: rural prices move toward nearby urban levels across all product types, consistent with stronger food demand in connected rural areas.

Household-level evidence supports this interpretation. Mobile adoption in covered areas increases food spending, consumed and purchased quantities, and reduces self-consumption, especially among rural and agricultural households. These effects operate largely through income diversification into off-farm and non-agricultural activities, and greater financial inclusion via mobile money, which together relax liquidity constraints faced by households. In this sense, connectivity acts not only as a coordination technology for farmers and traders, but also as a catalyst of rural transformation, with the resulting local demand expansion becoming an driver of market integration.

At the same time, our results highlight important distributional and general-equilibrium consequences. Households with few or no mobile phones in connected areas—particularly rural non-agricultural households—face higher food prices without commensurate gains in income diversification or off-farm opportunities. For these non-adopters, network coverage is associated with lower real food consumption, revealing a negative externality and showing that the aggregate effect of network arrival masks offsetting gains and losses within the same local economy.

Taken together, the findings suggest that mobile connectivity in West Africa generates a layered pattern of food market integration: supply-side arbitrage dominates over long distances, while rural-urban price catch-up and demand-side adjustments are observed at finer spatial scales. These forces operate through general-equilibrium adjustments across food, labor, and financial markets, with welfare gains concentrated among connected households. Policy should therefore tackle not only the *coverage gap* but also the *usage gap*. Expanding affordable handset access, digital skills, and mobile money usage—alongside support for small non-farm enterprises—will be critical to ensuring that the continued digitalization of rural economies fosters broad-based and inclusive development, rather than deepening disparities between adopters and non-adopters.

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Appendix

A.1 Variable Descriptive statistics.

A.1.1 Dependent variables

Table. A.1.1.1. Summary statistics of dependent variables

Variables	# obs.	Mean	SD	Min	Max
Price (XOF/gram)					
Sugar	12,425	0.65	0.51	0.010	24.27
Fresh onions	12,586	0.64	0.45	0.021	8.67
Salt	10,669	0.24	0.26	0.0004	9.48
Chili pepper	9,896	2.21	2.09	0.18	18.36
Fresh tomatoes	8,307	0.68	0.66	0.003	10.32
Imported rice	6,099	0.42	0.16	0.03	7.86
Quantity of commodity j purchased / household (HH) member in the last 7 days (grams, ln):					
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
Quantity of commodity j consumed / HH member in the last 7 days (grams, ln):					
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	25,855	4.85	0.94	1.25	10.08
HH spending / HH member (XOF, annual):					
Food spending	59,318	239,927	198,540	5060.2	6,231,026
Non-food spending	59,318	231457	297411	7067.7	1.37e+07
Off/on-farm activities:					
% HH (adult aq.) in off-farm work	57,683	0.26	0.28	0	1
% HH (adult aq.) in on-farm work	57,632	0.19	0.25	0	1
Number of non-agricultural enterprises in the HH	56,611	0.81	0.96	0	28
Sales of processed merchandises (XOF)	31,767	37,442	98,820	0	1,465,580
Margin unprocessed merch. trade (z-score)	31,767	3.86e-10	1	-4.524	5.033

Source: Authors' calculations based on LSMS (World Bank/WAEMU). Notes: Not all commodities and associated statistics are shown in the table. Only the first price record and only selected commonly-traded traded/consumed commodities' prices are reported. Product prices include various measurement units for a given product. Price, spending and sale variables are winsorized at the 99th and deflated using spatial and temporal deflators.

A.1.2 Digital connectivity variables

A.1.3 Instrumental variable

Table. A.1.2.2. Summary statistics for connectivity 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
Network connectivity:						
Mobile internet network distance, km (ln)	EA	4,769	1.46	1.60	0	5.76
Dummy internet network distance < 2km	EA	4,768	0.52	0.50	0	1
Dummy internet network distance < 5km	EA	4,766	0.57	0.49	0	1
Years since network arrival (<2km)	EA	4,731	1.83	1.92	0	10
# of operator signals well captured (<2km)	EA	4,768	1.22	1.38	0	5

Source: Authors' calculations based on EHCVM (World Bank/WAEMU). Notes: The distance variable is expressed in natural logarithms in the econometric analysis. [*] Not used in the analysis, included for comparison purpose.

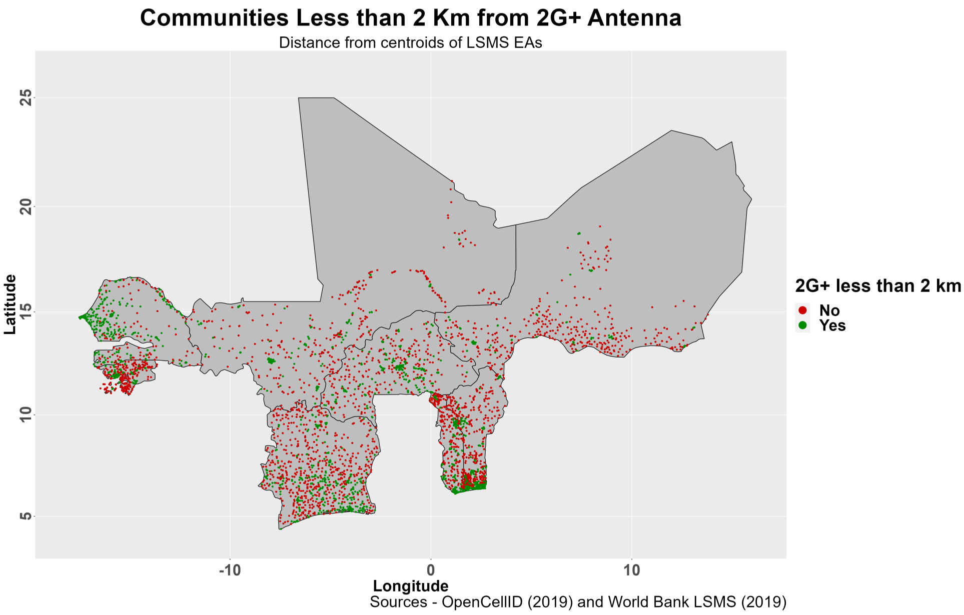

Fig. A.1.2.1. Network coverage in the WAEMU (≤ 2km).

Table. A.1.3.3. IV Descriptive Statistics

Variable	# obs (EA)	Average	Std. dev.	Min	Max
Z_z	4,774	0.000083	0.000242	0	0.003641
Daily lightning density	4,775	0.00796	0.01651	0	0.1143522
Pop density 2015	4,774	1221.72	3602.84	0.13176	34,944.11

Source: Authors' calculations based on lightning and population data from NASA.

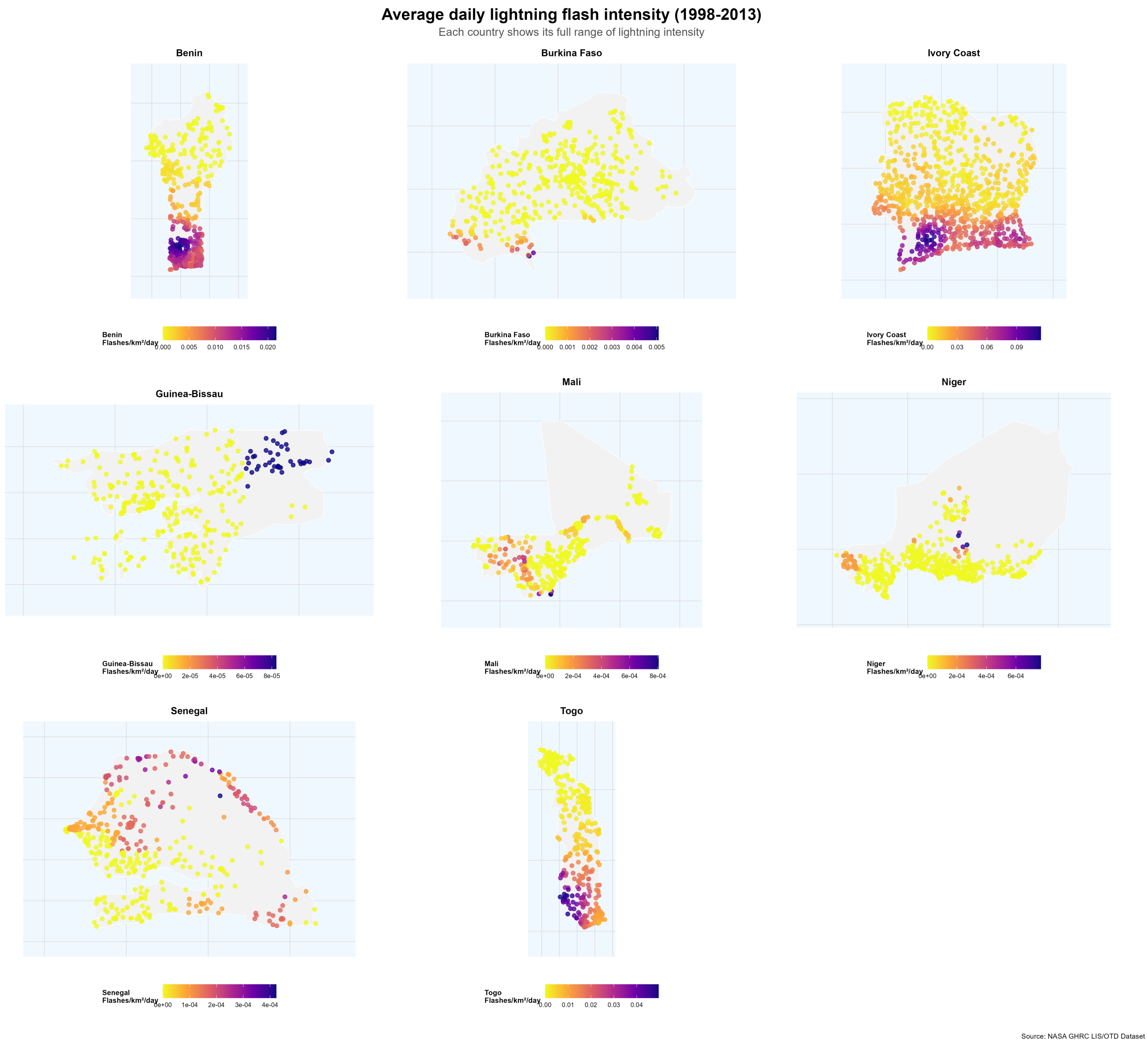

Fig. A.1.3.2. Mapping lightning strikes density in the WAEMU, 1998-2013 daily average.

A.2 Additional estimations

A.2.1 Mobile network connectivity and food product market prices

Table. A.2.1.1. Impact of 2G+ network proximity on food product prices (log, XOF/gram): IV, Reduced form, and OLS.

	(1)	(2)	(3)	(4)
Dep. var.: $\ln p(XOF)$	**2nd-stage estimates**		**Reduced form**	**OLS estimates**
CON_z (<2km, 0/1)				−0.002 (0.002)
CON_z (<5km, 0/1)	0.0398*** (0.0125)			
CON_z (<12km, 0/1)		0.0606*** (0.0192)		
Dist. to urban center (km, ln)	0.0080*** (0.0014)	0.0084*** (0.0016)		0.004*** (0.001)
Contemp. rainfall	−0.0232*** (0.0036)	−0.0225*** (0.0036)		−0.024*** (0.004)
Past rainfall (Av. 2015–2019)	0.0322*** (0.0055)	0.0303*** (0.0055)		0.034*** (0.005)
Nighttime light	−0.0003*** (0.0001)	−0.0003*** (0.0001)		−0.000*** (0.000)
Pop. density	−0.0000*** (0.0000)	−0.0000*** (0.0000)		−0.000*** (0.000)
EA pop. size (ln)	−0.0038*** (0.0005)	−0.0038*** (0.0005)		−0.003*** (0.000)
	1st-stage estimates			
IV	−273.51*** (6.94)	−180.95*** (10.11)	−10.97*** (3.36)	
Dist. to urban center (ln km)	−0.0998*** (0.0012)	−0.0723*** (0.0011)	0.0040*** (0.0005)	
Contemp. rainfall	−0.0214*** (0.0048)	−0.0271*** (0.0040)	−0.0241*** (0.0034)	
Past rainfall (Av. 2015–2019)	0.0391*** (0.0129)	0.0575*** (0.0113)	0.0337*** (0.0053)	
Nighttime light	0.0030*** (0.0001)	0.0017*** (0.0001)	−0.0002*** (0.0001)	
Pop. density	−0.0000*** (0.0000)	−0.0000*** (0.0000)	−0.0000*** (0.0000)	
EA pop. size (ln)	0.0152*** (0.0009)	0.0102*** (0.0008)	−0.0032*** (0.0005)	
District × product × unit FEs	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes
Observations	346,241	346,377	346,377	346,267
R-squared	-0.001	-0.004	0.002	0.819
AR F-stat	0.00146	0.00132		
KP Wald F-stat	1553	320.1		
LM-weak	351.4	215.9		

Notes: Robust standard errors in parentheses, one-way or two-way clustered at indicated level(s). First CON_z refers to 2G+ network proximity variables. Prices p are food product prices deflated by EA-level spatial deflators and temporal deflators. Reported first-stage statistics robust to heteroskedasticity and clustering. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.2.2 Internet connectivity and HH food demand

A.2.3 Mobile-enabled services

Table. A.2.2.1. **Internet connectivity and food spending per HH member**

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	**Food spending per household member (XOF, ln)**					
	All HHs		Urban		Rural	
CON 2G+ z (0/1) $\times$ Internet (0/1)	0.129**		0.125		0.216	
	(0.065)		(0.098)		(0.181)	
CON 3G+ z (0/1) $\times$ Internet (0/1)		0.121**		0.118		0.230
		(0.061)		(0.092)		(0.194)
Internet access (0/1)	−0.072	−0.060	−0.099	−0.092	−0.075	−0.059
	(0.045)	(0.039)	(0.088)	(0.081)	(0.078)	(0.065)
# mobile phones	0.014***	0.014***	0.016***	0.016***	0.017***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Observations	56,234	56,246	23,135	23,135	33,099	33,111
KP Wald F-stat	92.17	93.75	50.27	51.59	13.05	11.89
LM-weak	44.21	52.67	14.53	16.18	9.511	9.771

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered by EA. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All estimations include EA and survey wave FEs. Control variable estimates not reported. Second stage estimats reported. Control variables additionally include non-food spending per household member (XOF, ln).

Table. A.2.3.1. **Financial inclusion in the WAEMU.**

Variable	**Obs**	**Mean**	**Std. dev.**	**Min**	**Max**
Standard bank account ownership (0/1)	58,683	0.15258211	0.3599815	0	1
Postal bank account ownership (0/1)	58,683	0.01535805	0.1245218	0	1
Microfinance account ownership (0/1)	58,683	0.0585361	0.2358145	0	1
MM account ownership (0/1)	58,683	0.3426857	0.4746125	0	1
Prepaid card ownership (0/1)	58,683	0.0124568	0.1109135	0	1

Source: LSMS-EHCVM.

A.2.4 Income diversification

Table. A.2.4.1. Mobile connectivity and off-farm and on-farm labor force participation, IV estimations.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	% HH members with on-farm income			% HH members with off-farm income		
	All HHs	Urban	Rural	All HHs	Urban	Rural
CON_z × # mob.	0.065***	0.050**	0.176***	0.089***	0.064**	0.289***
	(0.014)	(0.021)	(0.067)	(0.020)	(0.032)	(0.110)
# Mobile phones	−0.036***	−0.044**	−0.056**	−0.047***	−0.043	−0.091**
	(0.009)	(0.020)	(0.023)	(0.013)	(0.031)	(0.038)
Observations	56,231	23,132	33,099	55,293	22,239	33,054
KP Wald F-stat	101.3	47.19	11.61	101.3	47.19	11.61
KP rank LM-stat	65.73	21.48	9.360	65.73	21.48	9.360

Notes: Robust standard errors clustered at the EA level in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All estimations include EA and survey wave FEs. CON_z is a dummy indicating whether the EA is located within 2km of a 2G+ cell-tower. Estimates instrumented by population-weighted lightning strike density interacted with the number of mobile phones. All specifications include household controls, EA and survey wave fixed effects.

Table. A.2.4.2. Mobile connectivity and non-agricultural revenues, IV estimations.

	(1)	(2)	(3)	(4)	(5)
Dep. Var. :	Margins in unprocessed merchandise sales (XOF, z-score)				
Sample:	All HHs	Urban	Rural	Non agr.	Agr.
CON_z × # mob.	0.215***	0.232*	0.494**	0.099	0.637***
	(0.057)	(0.126)	(0.211)	(0.162)	(0.198)
# Mobile phones	−0.112***	−0.182	−0.156**	−0.069	−0.209***
	(0.037)	(0.119)	(0.073)	(0.151)	(0.070)
# yrs since 1st enterprise	0.011***	0.014***	0.010***	0.012***	0.009***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Observations	56,234	23,135	33,099	21,784	33,574
KP Wald F-stat	101.2	47.21	11.55	68.14	17.57
KP rank LM-stat	65.61	21.48	9.315	48.77	13.15
	(6)	(7)	(8)	(9)	(10)
Dep. Var.:	Sales of processed merchandise (XOF, ln)				
Sample:	All HHs	Urban	Rural	Non agr.	Agr.
CON_z × # mob.	−0.382	−0.428	−1.193	−0.075	−1.462**
	(0.252)	(0.497)	(0.846)	(0.646)	(0.719)
# Mobile phones	0.388**	0.503	0.533*	0.140	0.665**
	(0.168)	(0.471)	(0.300)	(0.609)	(0.264)
# yrs since 1st enterprise	0.125***	0.070***	0.156***	0.072***	0.159***
	(0.005)	(0.008)	(0.007)	(0.008)	(0.007)
Observations	56,234	23,135	33,099	21,784	33,574
KP Wald F-stat	101.2	47.21	11.55	68.14	17.57
KP rank LM-stat	65.61	21.48	9.315	48.77	13.15

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered by EA. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All estimations include EA and survey wave FEs. CON_z is a dummy indicating whether the EA is located within 2km of a 2G+ cell-tower. Control variable estimates not reported.

A.3 Robustness checks

A.3.1 Augmented network coverage variables

Table. A.3.1.1. Network earliness, signal quality, and food price levels. IV estimations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Dep. Var.:	**Food prices (XOF/gram, ln)**							**Food price gap (%)**			
								Gap < 0	Gap > 0	Gap < 0	Gap > 0
Network earliness (# years) <2km	0.010***					0.016***		−0.012**	0.062***		
	(0.003)					(0.004)		(0.005)	(0.017)		
Tot. # WC networks <2km		0.016***					0.027***			−0.018*	0.125***
		(0.005)					(0.006)			(0.009)	(0.028)
1+ WC networks <2km			0.041***								
			(0.013)								
2+ WC networks <2km				0.047***							
				(0.015)							
3+ WC networks <2km					0.051***						
					(0.016)						
Network earliness (# years) × urb (0/1)						−0.020***		0.001	−0.145***		
						(0.005)		(0.007)	(0.020)		
Tot. # WC networks <2km × urb (0/1)							−0.036***			0.001	−0.262***
							(0.009)			(0.013)	(0.036)
Dist. Urban center (km, ln)	0.008***	0.009***	0.008***	0.009***	0.008***						
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)						
Urban area (0/1)						0.005	0.009	−0.128***	−0.131***	−0.125***	−0.206***
						(0.010)	(0.011)	(0.015)	(0.033)	(0.018)	(0.023)
District × product-unit FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	345,372	346,267	346,267	346,267	346,267	345,372	346,267	146,814	155,997	147,104	156,456
KP Wald F-stat	1513	1292	1516	1065	1162	818.3	546.9	428.2	490.6	264.5	372.8
LM-weak	364.2	348.9	393.2	325.9	315.5	515.6	570.5	293.4	334.9	295.9	353.1

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered by EA. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Control variable estimates not reported. $\#WC < 2$km refers to the number of "Well-Captured" (WC) network signals located within 2 kilometers of the nearest 2G+ tower. Network earliness denotes the number of years since the establishment of the first 2G+ tower within 2 kilometers of the EA.

Table. A.3.1.2. **Network earliness, signal quality, and household food spending. IV estimations.**

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:	**Food spending per HH member (XOF, ln)**				
Network earliness (# years) $<$ 2km $\times$ # mob.	0.034***				
	(0.008)				
1+ WC networks $<$2km $\times$ # mob.		0.120***			
		(0.027)			
2+ WC networks $<$2km $\times$ # mob.			0.129***		
			(0.029)		
3+ WC networks $<$2km $\times$ # mob.				0.148***	
				(0.034)	
Tot. # WC networks $<$2km $\times$ # mob.					0.041***
					(0.009)
# mobile phones	−0.071***	−0.394***	−0.313***	−0.211***	−0.243***
	(0.019)	(0.112)	(0.113)	(0.079)	(0.067)
Controls	Yes	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes
Product-unit FEs	Yes	Yes	Yes	Yes	Yes
Observations	55,800	56,246	56,246	56,246	56,246
KP Wald F-stat	84.36	106.1	92.34	66.44	102.4
LM-weak	60.86	79.03	71.16	61.60	83.12

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered by EA. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Control variable estimates not reported. Control variables additionally include non-spending per household member (XOF, ln), but results are robust to this variable exclusion. $\#WC <$ 2km refers to the number of "Well-Captured" (WC) network signals located within 2 kilometers of the nearest 2G+ tower. Network earliness denotes the number of years since the establishment of the first 2G+ tower within 2 kilometers of the EA.

A.3.2 Testing the exclusion restriction

Table. A.3.2.1. **Over-identification test, baseline estimations.**

Dep. var: Food prod. prices (ln)	(1) 2nd stage	(2) 1st stage	(3) 2nd stage	(4) 1st stage
CON_z (km, ln)	-0.014***		-0.015***	
	(0.004)		(0.004)	
Lightning IV		1,232.868***		145.461***
		(65.300)		(44.811)
Lightning IV^2		-171,363.576***		
		(20,269.827)		
Lightning IV × Altitude				3.821***
				(0.286)
Altitude			0.000	0.001***
			(0.000)	(0.000)
Controls	Yes	Yes	Yes	Yes
District × product FEs	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes
Observations	346,377	346,377	346,377	346,377
KP Wald F-stat	1141		852.1	
LM-weak	629.8		662.2	
Hansen-J pval	0.953		0.520	

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered by EA. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. CON_z is the distance (km, ln) to the closest 2G+ cell tower. Control variable estimates not reported.

Table. A.3.2.2. Network connectivity and food spending, placebo test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	**Food spending per HH member (XOF, ln)**							
	Early adopters		**Late adopters**		**Early adopters**		**Late adopters**	
	2nd-stage	1st-stage	2nd-stage	1st-stage	2nd-stage	1st-stage	2nd-stage	1st-stage
CON_z × # mob.	1.997		-0.115^{***}		-3.828		-0.083^{***}	
	(3.645)		(0.033)		(22.495)		(0.022)	
# mob.	-6.447		0.010		12.323		0.040^{***}	
	(11.67)		(0.011)		(72.51)		(0.008)	
IV		-47.894		870.16^{***}		14.703		830.20^{***}
		(88.00)		(105.24)		(86.05)		(101.00)
Controls	No	No	No	No	Yes	Yes	Yes	Yes
EA FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,798	12,798	34,373	34,373	12,596	12,596	34,114	34,114
KP Wald F-stat	0.296		68.37		0.0292		67.56	
LM-weak	0.302		34.32		0.0291		33.06	

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered by EA. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. CON_z is the distance (km, ln) to the closest 2G+ cell tower. Control variable estimates not reported. Early adopters are households who acquired their first mobile device before the network arrives. Late adopters are those who acquired their first mobile device before the network arrives.

Online Appendix

OA.1 Additional descriptive statistics.

OA.1.1 Traded products

Table. OA.1.1.1. Classification of 15 most-traded product–unit pairs by perishability

Product	Category	Rationale / Notes
Fresh tomato	Perishable	High water content; spoils within days.
Fresh okra	Perishable	Rapid spoilage (2–3 days).
Fresh onion	Perishable	Degrades quickly when traded fresh.
Whole chicken	Perishable	Fresh meat; requires refrigeration.
Pepper	Perishable	Fresh pods, high moisture; short shelf life.
Beef	Perishable	Fresh meat; highly perishable in tropical climate.
Red palm oil	Semi-perishable	Oxidizes over months; moderately stable.
Peanut butter	Semi-perishable	Prone to rancidity over time.
Potato	Semi-perishable	Can be stored for weeks; quality declines.
Afintin / Soumbala	Semi-perishable	Fermented; keeps weeks to months.
Salt	Non-perishable	Dry mineral, indefinite shelf life.
Sugar	Non-perishable	Dry, highly stable under ambient storage.
Tomato paste	Non-perishable	Processed and sealed; long shelf life.
Imported long grain / broken rice	Non-perishable	Dried staple; easily stored.
Peanut oil	Non-perishable	Refined oil; stable for months under shade.

Note: Classification based on FAO et al. (2011) and Hodges et al. (2011). Perishables spoil within days; semi-perishables are storable for weeks to a few months; non-perishables can be stored for extended periods without refrigeration.

Table. OA.1.1.2. Most-traded product-unit pairs: number of EAs trading the product-unit pair.

Prod.-unit pairs 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

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Table. OA.1.1.2 (continued): Most-traded product-unit pairs

Prod.-unit pair (by trading occurrence)	BFA	BEN	CIV	GNB	MLI	NER	SEN	TGO	# EAs
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

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Table. OA.1.1.2 (continued): Most-traded product-unit pairs

Prod.-unit pair (by trading occurrence)	BFA	BEN	CIV	GNB	MLI	NER	SEN	TGO	# EAs
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. - 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

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Table. OA.1.1.2 (continued): Most-traded product-unit pairs

Prod.-unit pair (by trading occurrence)	BFA	BEN	CIV	GNB	MLI	NER	SEN	TGO	# EAs
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 - 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. - 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

Notes: Product-unit pairs ordered by trading occurrence in enumeration areas (EAs). The last column is the total number of EAs trading the pair.

OA.1.2 Control variables

Table. OA.1.2.1. Household control variables, descriptive statistics.

Variable	# obs	Average	Std. dev.	Min	Max
Panel A. HHH characteristics:					
No education (0/1)	59,318	0.5998785	0.4899269	0	1
Primary education (0/1)	59,318	0.1809318	0.3849649	0	1
Secondary gen 1 (0/1)	59,318	0.095965	0.2945458	0	1
Secondary gen 2 (0/1)	59,318	0.0530178	0.2240708	0	1
HHH literacy (0/1)	59,318	0.4863365	0.4998175	0	1
HHH gender (0/1)	59,318	1.189956	0.3922698	1	2
HHH age	59,318	45.63658	14.66437	12	105
Married monogamous (0/1)	59,316	0.5876489	0.4922619	0	1
Married polygamist (0/1)	59,316	0.1872913	0.3901484	0	1
Panel B. HH demographic characteristics:					
Household size	59,318	6.171148	4.167168	1	59
Panel C. HH Housing characteristics:					
Tenant (0/1)	59,318	0.1627138	0.3691075	0	1
Wall in final materials (0/1)	59,318	0.6710469	0.4698369	0	1
Roof in final materials (0/1)	59,318	0.7518302	0.4319545	0	1
Floor in final materials (0/1)	59,318	0.6477683	0.4776697	0	1
Panel D. HH living standards:					
TV (0/1)	59,318	0.3197429	0.4663808	0	1
Iron (0/1)	59,318	0.0406194	0.1974085	0	1
Fridge (0/1)	59,318	0.1014305	0.3019004	0	1
Kitchen (0/1)	59,318	0.04234	0.2013654	0	1
Computer (0/1)	59,318	0.0440775	0.205269	0	1
Decoder (0/1)	59,318	0.1343578	0.3410392	0	1
Owns car (0/1)	59,318	0.0286934	0.1669447	0	1
Banked (0/1)	59,318	0.169042	0.2653388	0	1
Panel E. Infrastructure access:					
Uses elec. grid (0/1)	59,318	0.3766236	0.4845433	0	1
Uses solar elec/genset. (0/1)	59,318	0.1989643	0.3992245	0	1
Improved waste disposal (0/1)	59,318	0.2687662	0.4433218	0	1
Improved toilets (0/1)	59,318	0.2592861	0.4382466	0	1
Improved human waste disposal (0/1)	59,318	0.2611923	0.4392882	0	1
Improved sewage disposal (0/1)	59,318	0.095071	0.2933155	0	1
Panel F. HH exposure to shocks:					
Idiosyncratic demographic shocks (0/1)	59,318	0.3519168	0.4775722	0	1
Idiosyncratic economic shocks (0/1)	59,318	0.1477123	0.3548176	0	1
Covariant natural shocks (0/1)	59,318	0.308473	0.4618669	0	1
Covariant economic shocks (0/1)	59,318	0.2327624	0.4225956	0	1
Covariant violence shocks (0/1)	59,318	0.0535251	0.22508	0	1
Other shocks (0/1)	59,318	0.0197411	0.1391103	0	1
Panel G. HH crop characteristics:					
Total area of plots / eq. adult (hectare, ln)	58,722	0.2509	401.1745	0	3.404

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%).

Table. OA.1.2.2. Enumeration Area (EA) or "community" control variables, descriptive statistics.

Variable	# obs	Mean	SD	Min	Max
Local development:					
Nighttime light density	4,618	13.737	17.812	2.85	63.00
Demography:					
Population density	4,618	1181.002	3536.618	0.13	34944.11
Number of inhabitants in the EA (ln)	4,618	7.861	1.279	0.00	13.12
Geography and climate:					
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
Contemporaneous rainfall	4,774	2.590	1.274	0.0529	7.155
Average past rainfall (2015-2019)	4,774	2.567	1.257	0.0614	7.030

Source: authors. Data from LSMS (World Bank/WAEMU); SEDAC Gridded Population of the World; Version 4 DMSP-OLS Nighttime Lights; LIS 0.1 Degree Very High Resolution Gridded Lightning Climatology Data Collection.

OA.1.3 Sample mean-test : Agricultural vs non Agricultural Households

Table. OA.1.3.1. Baseline differences between agricultural and non-agricultural households

	Non-agricultural HHs		Agricultural HHs		Diff. (0–1)
Variable	N	Mean	N	Mean	(mean_0–mean_1)
Panel A: All households					
Number of mobile phones	23,945	2.2709	35,373	1.8078	0.4631***
Food spending pc (XOF)	23,945	304,708	35,373	196,074	108,633***
Panel B: Rural households only					
Number of mobile phones	6,579	1.7773	27,846	1.6088	0.1685***
Food spending pc (XOF)	6,579	264,754	27,846	188,394	76,359***
N (all HHs)			59,318		
N (rural HHs)			34,425		

Notes: Panel A uses the full sample of households; Panel B restricts to rural households ($urbain = 0$). Means and differences are obtained from two-sample t-tests with equal variances. "Diff. (0–1)" reports the difference in means between non-agricultural (group 0) and agricultural (group 1) households. *** $p < 0.01$.

OA.2 IV estimations: Additional estimations and robustness checks.

OA.2.1 Alternative measure of mobile network access

Table. OA.2.1.1. **First-stage equation and alternative measures of mobile network access, OLS estimates.**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var:	**Distance to network (km, ln)**			**# Well-captured signals <2km (2G+ network)**			**Network earliness (years)**		
Lightning risk (IV)	1,244.676***	1,251.123***	792.912***	−1,129.976***	−1,132.390***	−618.309***	−1,590.989***	−1,592.879***	−1,029.420***
	(154.991)	(156.769)	(107.422)	(137.758)	(138.954)	(111.677)	(188.301)	(188.952)	(167.300)
Contemp. Rainfall		−0.045	0.052		−0.017	−0.114		0.129	0.028
		(0.075)	(0.069)		(0.079)	(0.071)		(0.105)	(0.095)
Av. Rainfall (2015–2019)		−0.268	−0.309		0.139	0.191		−0.059	0.001
		(0.219)	(0.188)		(0.176)	(0.147)		(0.268)	(0.232)
Nighttime light density			−0.014***			0.024***			0.024***
			(0.003)			(0.004)			(0.005)
Population density			0.000			−0.000			−0.000
			(0.000)			(0.000)			(0.000)
EA population size (ln)			−0.054***			0.091***			0.082***
			(0.015)			(0.016)			(0.027)
Dist. to the closest city (ln, km)			0.349***			−0.314***			−0.370***
			(0.022)			(0.020)			(0.027)
Constant	1.354***	2.160***	1.976***	1.315***	1.001**	0.661*	1.960***	1.776***	1.598***
	(0.013)	(0.522)	(0.451)	(0.011)	(0.392)	(0.345)	(0.016)	(0.610)	(0.580)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey wave FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,764	4,764	4,647	4,763	4,763	4,646	4,725	4,725	4,608
R-squared	0.649	0.650	0.748	0.496	0.496	0.648	0.474	0.474	0.572

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered by district. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.The variable "Network earliness (years)" is the number of years passed since the initial deployment of a cell tower within a 2km radius from the EA centroid.

OA.2.2 Alternative measure of lightning activity

Table. OA.2.2.1. Network proximity and food prices – 2SLS estimates using an alternative lightning density measurement.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. var.:	**Food prices (XOF/gram, ln)**				**$\|$Food price deviation$\|$ (%)**					
Price gap:							$Gap < 0$		$Gap > 0$	
Winsorization:					No	99%	No	99%	No	99%
Dist. 2G+ (<2km, 0/1)	0.017	0.044*	0.034	0.060***	−0.098***	−0.072***	−0.032**	−0.032**	−0.152	0.002
	(0.023)	(0.024)	(0.022)	(0.023)	(0.032)	(0.021)	(0.015)	(0.015)	(0.123)	(0.051)
Dist. 2G+ × urb.			−0.024	−0.026	0.203***	0.117***	0.026*	0.026*	0.227*	0.101*
			(0.018)	(0.019)	(0.062)	(0.019)	(0.014)	(0.014)	(0.118)	(0.052)
Urban (0/1)			−0.024*	−0.025*	−0.234***	−0.155***	−0.011	−0.011	−0.353***	−0.252***
			(0.014)	(0.015)	(0.043)	(0.015)	(0.011)	(0.011)	(0.089)	(0.044)
Observations	346,267	356,546	346,267	356,546	317,513	317,513	228,465	228,465	69,014	69,014
District × prod.-unit FEs	Yes	No	Yes	No	Yes					
District FEs	No	Yes	No	Yes	No					
Product-unit FEs	No	Yes	No	Yes	No					
AR F-stat	0.473	0.0659	0.124	0.0122	0.00104	4.92e−09	0.0293	0.0293	0.117	0.147
KP Wald F-stat	120.8	133.3	57.25	62.99	46.80	46.80	42.08	42.08	27.28	27.28
LM-weak	536.1	586.8	484.1	516.5	478.7	478.7	362.5	362.5	249.4	249.4

Notes: Standard errors in parentheses, robust to heteroskedasticity and clustered at the district-product level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Dist. 2G+ denotes the presence of a 2G+ tower within 2km of the EA. FPG is the absolute difference between EA-level price and the district urban prices. In this series of estimations, Z_z is the 1998-2013 averaged annual number of lightning strikes per km^2, weighted by population density.

OA.2.3 First-stage estimates sensitivity to the population weighting factor

Table. OA.2.3.1. Instrument sensitivity to population weighting factor, OLS estimates, Eq.(4).

	(1)	(2)	(3)	(4)	(5)
Dep. Var.:		CON_z (km, ln)		Z_z	CON_z (km, ln)
Z_z		1,251.123***	1,236.333***		
		(156.769)	(154.407)		
$\perp Z_z$					1,236.333***
					(154.260)
Population density	−0.000037*		−0.000034*	-2.58×10^{-9} **	
	(0.00002)		(0.000019)	(1.24×10^{-9})	
Contemp. Rainfall	−0.0455	−0.0453	−0.0477	1.72×10^{-6}	−0.0429
	(0.0755)	(0.0745)	(0.0749)	(8.95×10^{-6})	(0.0745)
Av. Rainfall (2015–2019)	−0.2384	−0.2680	−0.2618	1.8×10^{-5}	−0.2449
	(0.2224)	(0.2189)	(0.2182)	(3.8×10^{-5})	(0.2191)
Observations	4,764	4,764	4,764	4,764	4,764
R-squared	0.64	0.65	0.65	0.73	0.65

Notes: Standard errors in brackets, robust to heteroskedasticity and clustered by district. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All estimations include district and survey wave fixed effects. $\perp Z_z$ refers to the orthogonalized IV, that is, the residuals from the estimation in column (4).

OA.2.4 Dealing with spatial anonymization

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 EHCVM-LSMS survey. We then extracted the average annual number of lightning strikes within each administrative district.

Table. OA.2.4.1. Mobile connectivity and food prices, dealing with spatial anonymization

	(1)	(2)	(3)	(4)
Dep. var.:	Food product prices (XOF/gram, ln)			
	Bilinear extraction		Polynomial extraction	
CON_z (<2km, 0/1)	0.040***	0.055***	0.049***	0.060***
	(0.013)	(0.014)	(0.013)	(0.014)
CON_z × Urban (0/1)		−0.071***		-0.085***
		(0.017)		(0.019)
Controls	Yes	Yes	Yes	Yes
Observations	346,267	346,267	319,775	319,775
KP Wald F-stat	1335	649.7	995.1	445.2
LM-weak	378.8	551.5	361.9	599

Notes: Robust standard errors in parentheses, clustered by district-product. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All estimations include district-product-unit and survey wave fixed effects.

OA.2.5 Country sensitivity tests

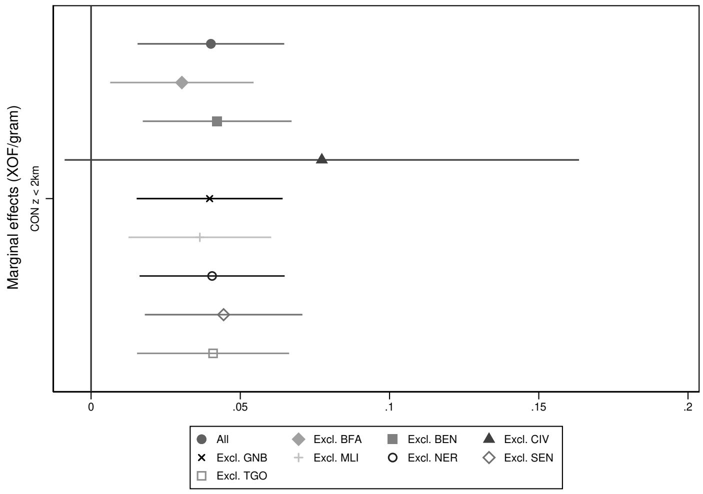

Fig. OA.2.5.1. Network connectivity and food price levels, IV estimations sequentially excluding countries.

Note: 95%-confidence intervals reported. Excluding Côte d'Ivoire reduces the sample size by 21%. Instrument strength remains above conventional level, with a minimum KP Wald F-statistic equal to 31.68 when excluding Côte d'Ivoire.

OA.3 Raster Dataset Specifications and shock variables definition.

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.

Population density.

Database: SEDAC Gridded Population of the World. Resolution:

- Net CDF-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)

Nighttime light density density.

Database: Version 4 DMSP-OLS Nighttime Lights. Resolution:

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

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

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)

OA.4 Handling non-standard measurement units.

OA.4.1 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 Figure OA.4.1.1), 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.

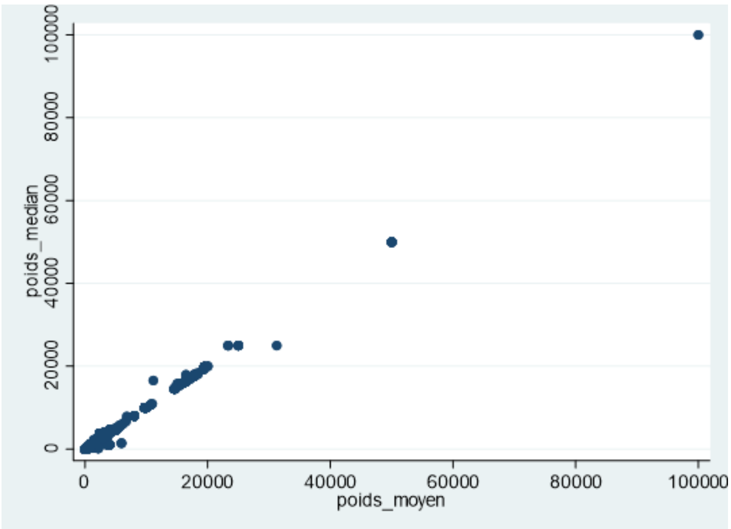

Fig. OA.4.1.1. **Correlation between average- and median-based conversion factors for quantities of food consumed by households in Burkina Faso.**

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

Pascal

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