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Can Mobile Technologies Enhance Productivity? A Structural Model and Evidence from Benin Food Suppliers

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A Structural Model and Evidence from Benin Food Suppliers

Prepared by Pierre Nguimkeu and Cedric Okou

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ABSTRACT: The paper analyzes the drivers of digital technologies adoption and how it affects the productivity of small-scale businesses in the grains and legumes markets in Africa. We collect data from two semi-rural markets in Benin, where grains and legumes are key staple foods and one-third of the population has internet access. We develop a structural model to rationalize digital technology adoption—defined as the use of mobile broadband internet connection through smartphones—as well as usage patterns and outcomes observed in the data. The model's implications are empirically tested using both reduced-form and structural maximum likelihood estimations. We find that younger, wealthier, more educated grains and legumes suppliers and those closely surrounded by other users are more likely to adopt digital technologies. Adopters perform 4-5 more business transactions each month than non-adopters on average, suggesting that digital technology adoption could raise the monthly frequency of trades by up to 50%. Most adopters are women, but their productivity gains are lower than their male counterparts. Counterfactual policy simulations with the estimated model suggest that upgrading the broadband internet quality yields the largest improvement in adoption rate and productivity gains, while reducing its cost for a given connection quality has a moderate effect. Improving access to credit only increases the adoption rate of constrained suppliers.

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WORKING PAPERS

Can Mobile Technologies Enhance Productivity? A Structural Model and Evidence from Benin Food Suppliers*

Prepared by Pierre Nguimkeu[1], and Cedric Okou[2]

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1 Introduction

Food security remains an important development goal in Africa, a region where one in five people were chronically undernourished and 24% of the people were acutely food insecure in 2023 (FAO et al., 2023). Beyond the production and availability of food, a range of market frictions can impede the continuous supply of safe, sufficient, affordable, and nutritious food, with disproportionate negative effects on households at the lower end of the income distribution.[1] These frictions include bottlenecks to market access, transport infrastructure gaps, limited product information, constrained storage capacity, heavy reliance on rainfed agriculture, and widespread unmechanized small scale farming, among other stressors of food security (Fafchamps, 1993; Gollin and Rogerson, 2016). However, the rapid uptake of mobile phones and broadband internet in Africa, which contributed to a wider adoption of digital technologies, has the potential of facilitating the market access of food products, and thereby improve food security (Aker, 2010; Conley and Udry, 2010; Hjort and Poulsen, 2019). This paper analyzes how digital technology adoption shapes the productivity of small scale businesses in the grains and legumes markets. These commodities play a crucial role in feeding households and reducing food insecurity in developing countries, especially in Africa (Gollin, 2010; Gollin and Udry, 2021). Our data are from Benin, a West African country where one-third of the population had used internet in 2022.[2] The penetration of mobile broadband connections, which was very limited a decade ago, rose sharply from 1.5% of the country's population in 2013 to reach 42% in 2022 (International Telecommunication Union, 2022). The number of cellular subscriptions in Benin has also reached a record-high of 109 per 100 people in 2022. Despite this striking progress, relatively high costs and unreliable networks may hinder faster adoption of digital technologies in Benin and raise questions about their expected beneficial effects on food supply and trade in local food markets (Aker and Mbiti, 2010; Nguimkeu and Okou, 2021).[3]

To understand the local economic behavior, we conducted a random survey to collect field data on mobile technology usage, individual characteristics, and business outcomes among grains and legumes suppliers in two semi-rural markets in Benin. Our survey data reveal that about 45% of respondents use their mobile broadband connections to navi-

[1]In Africa, about 40% (up to 60%) of the average (poorest) households' spending in on food. Climate shocks, supply disruption of agricultural inputs (seeds, fertilizers, fuels), and trade restrictions (quotas and tariffs) in source countries are additional stressors of food security. Together with food supply, demand side factors such as consumption, diets, and income shape food insecurity dynamics (Okou et al., 2022).

[2]According to the International Telecommunication Union (2022)'s definition, internet users refer to individuals who have used the internet via a digital device (computer, mobile phone, personal digital assistant, digital TV, etc.) from any location in Benin in the last 3 months of each fiscal year.

[3]The estimated cost of a basket comprised of the cheapest mobile broadband plans, providing at least 2 GB of monthly data and using at least 3G technology, was about 5.7% of Benin's GNI per capita in 2022 (International Telecommunication Union, 2022). This exceeded the average price (to per capita GNI ratio) of similar mobile broadband plans in Africa and was 4 times higher than the world average cost.

gate social media and digital applications, while 30% of them use it to effectively trade their products. The related connection costs are quite substantial, reaching one-fifth of the minimum monthly wage in Benin for the majority (54.1%) of the surveyed mobile broadband users. We first use these data to estimate the probability of digital technology adoption and its main drivers among food suppliers, where adopters are broadly defined as those that use mobile broadband internet connection to navigate digital applications and the social media through their smartphones. We also estimate the effect of adoption on productivity, proxied by the number of monthly market transactions. We find that younger, wealthier, more educated individuals and people surrounded by other digital technology users are more likely to adopt. On average, adopters perform 4-5 more transactions each month than non-adopters, everything else being equal. Given that non-adopters perform on average 10 transactions per month, this suggests that digital technology adoption could raise the monthly frequency of grains and legumes trades by up to 50%. While women adopt more, men tend to benefit more from these digital technologies. We find that male adopters perform 5.3 to 8.9 more transactions than their non-adopters counterparts, whereas female adopters perform only 1.6 to 3.0 more transactions than their non-adopters counterparts.

To guide the analysis of suppliers' behavior in local food markets, we develop a structural model which rationalizes the observed digital technology adoption and usage patterns in the data. The model features a continuum of heterogeneous suppliers of grains and legumes who differ by their entrepreneurial skills, their digital-specific productivity, and their initial wealth endowment that they may use as collateral to obtain credit. Their adoption decision depends both on these personal characteristics as well as the quality and cost of the broadband internet connection. The model implies that suppliers adopt digital technologies only if their digital-specific productivity exceeds a certain threshold, and this threshold is higher for credit constrained suppliers. Labor demand and firm profits are increasing both in wealth (for credit constrained suppliers) and in digital-specific productivity (for adopters). These theoretical results are consistent with the patterns observed in the survey data, and the structural maximum likelihood estimation of the model quantifies the elasticities between drivers of digital skills, production factors, wealth and output. In particular, we find that while aging is associated with lower digital skills, the latter increase by 10.3% with every additional year of education. Likewise, every additional user within a one-kilometer radius is associated with a 0.34% increase in digital skills. The total share of production inputs is close to 1, implying that the supply of grains and legumes is a competitive market. The estimated degree of credit constraints suggests that investment is bounded to less than 5.5 times the value of a food supplier's collateral.

Using the estimated model, we perform a set of counterfactual simulations to assess the implications of a range of policy options. We consider three main policy interventions aiming at: (i) improving the quality of connectivity, (ii) reducing the cost of internet, and (iii) relaxing credit constraints. We find that upgrading the broadband internet quality yields a sizeable improvement in digital adoption rate and productivity gains, while reducing its cost only has a moderate effect for a given quality, consistent with recent empirical findings (Elliott et al., 2024). In particular, increasing the quality of the network (proxied by internet area coverage and safety) by 35 percentage point can yield up to 100% adoption rate and 180% increase in average productivity. However, reducing the cost of internet to zero, making it unrealistically free for everyone, would increase the adoption rate only by 4 percentage points. Likewise, improving access to credit would increase the adoption rates only for few constrained suppliers. Allowing suppliers to borrow up to 4 times the value of the average wealth in the data increases the adoption rate by only 1 percentage point and lifts average productivity by 3.2%. In addition, no amount of credit is able to shift adoption rate beyond 58%. These results suggest that the quality of internet is the most critical incentive for adoption given its impact on profits, and gains from reducing the cost of access to the internet or access to credit will not be fully reaped unless the quality of internet connectivity is satisfactory.

These results broadly align with the view that the adoption of digital technologies, if complementary to input factors, can boost productivity and output (Akerman et al., 2015; Bartel et al., 2007; Brynjolfsson and Hitt, 1995). By enhancing labor and capital, newly adopted digital technologies can spur factor-biased technological change and improve the efficiency of production (Acemoglu, 1998, 2002; Violante, 2008). However, without complementary investment in skills and capital, the productivity gains of digitization could be at best marginal (Bartel et al., 2007; Emerick et al., 2016). For instance, Usai et al. (2021) argue that excessive investment in digital technologies may even shift investment away from complementary input factors, erode the relational capital, and hinder a firm's innovation potential and productivity. Our work also relates to studies by Comin and Hobijn (2004) and Chen (2020), who showed that technology adoption explains substantial differences in agricultural capital intensity between rich and poor countries. In the same vein, DePaula (2023) and Suri and Udry (2022), among others, use randomized field experiments to document productivity gains from digital technology adoption in agriculture. Our framework refines these existing studies in various important dimensions. First, we build a structural model which maps digital skills (driven by education, age and proximity to digital technology users), network effects and wealth to digital technology adoption. This flexible model allows to trace out the outcomes of various counterfactual policies, using structural parameters fitted with our survey data. Second, while most of the previous studies on digital technology adoption in Africa focus on the farmers and producers side (Suri and Udry, 2022; Oliva et al., 2020; Magruder, 2018; Aker and Ksoll, 2016; Koundouri et al., 2006), we focus our attention on the intermediaries (suppliers), who are key players in agricultural value chains and the main interface to consumers, in particular the vulnerable households. Third, our findings suggest that in semi-urban staple food markets – central to the provision of nutritious and sufficient diets to food insecure populations – the quality of the internet is a critical ingredient for productivity and well-being, while education and user social networks are reinforcing factors.

The remainder of this paper is organized as follows. Section 2 describes the data collection strategy and sheds a descriptive light on the uptake and usage of digital technologies by grains and legumes suppliers. In Section 3, we develop a simple model to rationalize the adoption of digital technology and elicit how it shapes the productivity and output of small scale businesses. Section 4 fits a reduced-form specification to empirically analyze the drivers of digital technology adoption and their effects on productivity. Section 5 takes the structural model to data, explores the key decision channels, and discusses policy options. Section 6 concludes.

2 Data and Background

The data we use in this paper come from a random survey which we ran from May to July 2023 to gather data from two semi-urban markets in Benin. Located in West Africa, Benin has a 121-kilometer-long coastline on the Gulf of Guinea, making this country a commercial hub and popular tourist destination. Benin's economy is reliant on the exports of agricultural products, mainly cotton which accounted for about two-thirds of total exports in 2022, and the reexport of imported goods such as used cars and rice to Nigeria—its largest regional trade partner. In addition to cash crops, subsistence staple foods are produced and traded in local food markets and along two major regional corridors—the West-East corridor from Lomé to Lagos and the South-North corridor from Cotonou to Niamey. The data collected in local markets in Benin is used to understand the background and relevance of our conceptual framework, and test its empirical relevance.

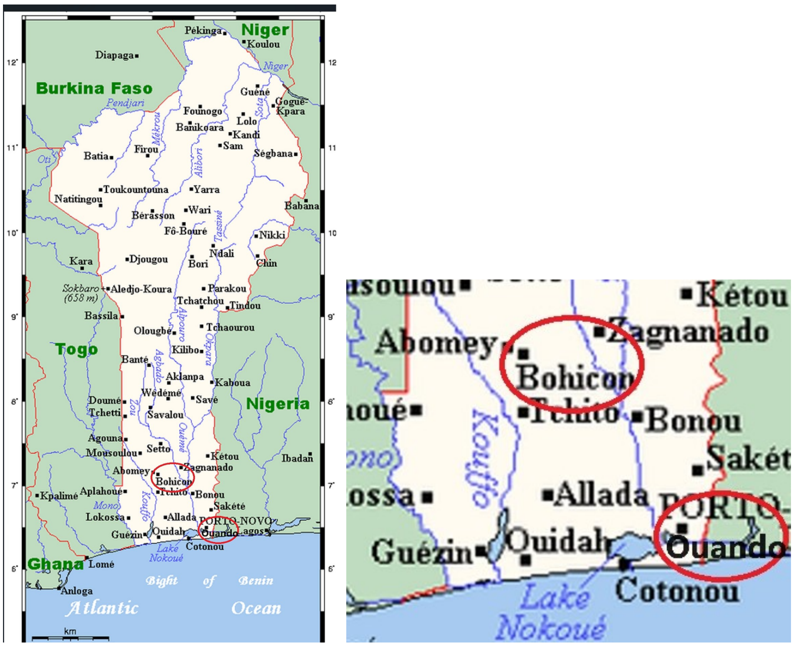
2.1 Data Collection

The survey was designed to collect information on digital technologies—specifically, broadband internet—adoption and usage. We ran this survey to fill the gaps in the existing data sources. Indeed, detailed information on digital technology adoption, connection costs, individual characteristics, business operations and outputs, and credit and market frictions was not yet available in standard household surveys or other national surveys conducted in Benin by statistical agencies, local stakeholders, and international organizations. We expressly targeted the grain and legume value chains, which are critical for curbing food insecurity. The survey was conducted in a rural market (Bohicon market) and semi-urban market (Ouando market) in Benin. The former is established in a small town of 171,781 people located about 124 kilometers north of Cotonou—Benin's biggest city and largest economic hub, while the latter sprawls 3.5 hectares in a relatively larger town of 264,320 people located 9 kilometers away from the capital city of Porto-Novo.[4] These are two major markets in Benin where a variety of staple grains

[4]The population size in Bohicon and Porto-Novo are taken from the 2013 Fourth General Population and Habitat Census, which was the latest census data available at the time we ran the survey. The Bohicon market takes place on Wednesdays and Sundays whereas the Ouando market takes place every

and legumes such as beans, maize, peanuts, cowpeas, and melon seeds are locally traded.

Figure 1: Map of Benin Highlighting the locations of Bohicon and Ouando Markets



Source: Wikipedia

Our sampling approach was based on the stratification strategy used in the latest census in Benin. First, we selected Bohicon and Ouando markets (our strata) because they are two representative (rural and semi-urban) grains and legumes markets in Benin. Second, we randomly interviewed grains and legumes suppliers from a list of potential respondents in each market. Of the collected data, we focus on 451 grains and legumes suppliers surveyed across Bohicon and Ouando markets. The survey gathered data on business characteristics and outcomes (e.g., sales, number of transactions, business ownership, business size); access and usage of digital technologies (e.g., social media, mobile money, internet browsing, Youtube, KasuwaGo app, weather); personal characteristics (e.g., age, schooling, experience, education and type of training, wealth); risk aversion (e.g., willingness to trade with new or different partners, willingness-to-pay to hedge against certain types of risk); access to credit (e.g., loan applications, type and amount of credit received, funding sources); and bad business experiences (e.g., scams, deception, loss of private information, previous business failures). In particular, the KasuwaGo app is a digital trading platform which was recently developed to facilitate interactions and trade among actors of the grains and legumes value chains, see Olabisi et al. (2024) for a thorough description of the app. Appendix A presents additional details on the survey design and implementation.

Tuesday, Thursday, and Saturday.

2.2 Descriptive Statistics

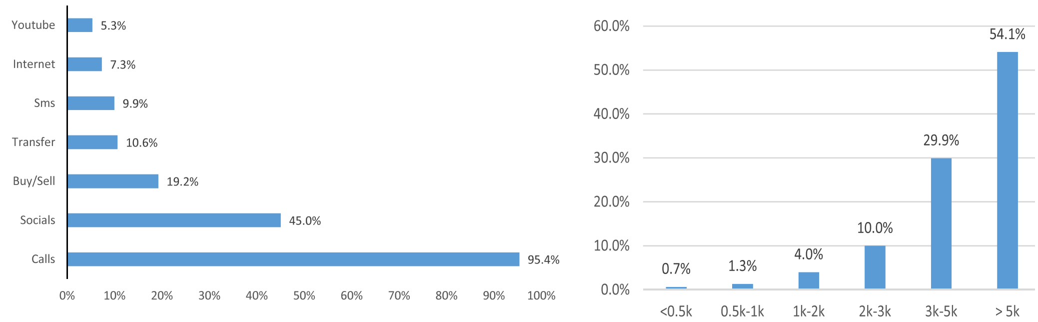
We describe the survey data and present some empirical evidence that sheds light on the adoption and usage of digital technologies among grains and legumes suppliers, as well as the role that these technologies play in the suppliers' entrepreneurial activities. This helps set the background to motivate and anchor our theoretical model. The data reports information about 451 suppliers in the the grains and legumes value chains distributed across Bohicon and Ouando markets, who are intermediaries between producers (farmers) and consumers (households or other retailers). Along these value chains, suppliers mainly trade locally sourced grains and legumes stored in small shops in local food markets. Among these suppliers, 81% are women and 87.4% are married with 5.1 children on average. This suggests that the trading of grains and legumes in our representative sample is dominated by women aged 22 to 75, which implies they are on average 45.8 years old. Women play crucial roles in agrifood systems, which absorb about 66% of working women in Sub-Saharan Africa (Costa et al., 2023). Moreover, about 60% of off-farm agrifood workers in the region are women who engage in various segments of agrifood systems as food processors and traders. In Benin, women are typically responsible for the post-harvest storage and processing of food products for domestic consumption and traditionally earn an income by trading agricultural products in local food markets (Miassi et al., 2018).

The average number of monthly transactions per traders is 11.6, and most of the respondents have more than 10 years of experience in the business (90% of the sample). The survey also documents their levels of education, years of experience in the grains and legumes business, and number of employees. Interestingly, more than half of the respondents (52%) do not have a formal training or education, about half of them employ 6 to 9 employees (49.9%), and most of the respondents have more than 10 years of experience (90%). Figure 2 presents the daily frequency of mobile phone usages as well as the monthly amount spent on digital applications among respondents. Almost all respondents (95.4%) use their mobile phones for calls, while close to half of them (45%) use their phones to navigate on social media. Nearly 30% of respondents use their phones to either trade products and/or make mobile money payments. We also find that 23.5% of respondents use digital technologies for other usages such as sending text messages, browsing internet, and watching YouTube. The respondents spend substantial amounts of money for broadband services. About 30% of the respondents spend between 2,000 and 5,000 CFA Francs monthly. Moreover, the majority of them (54.1%) spend more than 5,000 CFA per month, which represents about one-fifth of the minimum monthly wage in Benin.

Defining digital technology adopters

For the purpose of our study, we define "Non-Adopters" as grains and legumes suppliers that use their mobile phones only for basic calls and short message service texts. They typically do not use smartphones. We define "Adopters" as those who use their mobile phones for other uses including digital applications and social media. Accordingly, we

Figure 2: Digital Technologies Usage (left) and Spending (right)



Notes: The different usages are not mutually exclusive.

Source: Authors' survey and calculations

have a partition of 51% of Adopters—all of whom use android or smartphones, and 49% of "Non-Adopters"—most of whom only use simple phones. Table 1 reports the summary statistics of all respondents as well as non-adopters and adopters.

This stratification allows us to document four important facts. First, Adopters are on average more educated, perform more business transactions, and operate larger businesses, but are relatively younger with less business experience than their non-adopter counterparts. This suggests that adoption is potentially driven by education and can lead to more business opportunities and job creation (Aker and Mbiti, 2010; Houngbonon et al., 2022; Karaivanov and Yindok, 2022; Nguimkeu and Okou, 2021; Suri and Udry, 2022). In particular, two-thirds of non-adopters (66%) do not have formal education and none of them attended college. Second, adopters spend more money on mobile broadband services than non-adopters. The majority of non-adopters (53.2%) complain about the affordability of expensive mobile broadband service costs. This suggests that relatively high connection costs may impede a wider adoption of digital technologies by other potential users (Hauge and Prieger, 2010; Urama and Ogbu, 2018; Whitacre and Rhinesmith, 2016). Third, when counting the number of digital technologies users located nearby the respondent—within a 500-meter radius, we notice that respondents who are geographically close to many users tend to adopt digital technologies more than those that are not. This points to possible peer or network effects in technology adoption (Birke, 2009; Fafchamps, 2001). Fourth, we inquire about respondents' motivations for using (or not) these technologies. Their responses show (left panel of Figure 3) that almost all users are motivated by better access to market information such as prices and customers (89.4%) and easiness to communicate with their producers and clients (8%) (Aker, 2010). In contrast, the right panel of Figure 3 reveals that 25% of the respondents claim they are not interested in digital technologies, while 18.6% worry about privacy issues and lament about the reliability of the mobile broadband connectivity. This suggests that the quality and security of broadband connectivity are critically important

Table 1: Demographic and Business Characteristics of Adopters and Non-Adopters

	Non-Adopters	Adopters	All
Female (in %)	80.009	81.739	80.931
Age (in years)	48.638	43.191	45.841
Married (in %)	85.067	89.565	87.361
# of Children	6.1262	6.0617	6.0924
Wealth (in 100,000 CFA)	9.043	10.522	9.797
# of Nearby users	20.973	27.957	24.534
Member of association (in %)	64.220	68.696	66.518
Native (in %)	80.995	77.826	79.379
Education			
Primary	27.15	28.7	27.94
Secondary/Technical	6.79	28.7	17.96
Tertiary education	0.00	3.91	2.00
No formal education	66.06	38.7	52.11
Experience (# years)			
2 - 5	1.36	1.32	1.34
5 - 10	5.43	11.89	8.71
10+	93.21	86.78	89.96
# Transactions	10.095	13.052	11.603
Business size (# employees)			
1 - 2	1.46	3.96	2.77
3 - 5	34.95	37.89	36.49
6 - 9	55.34	44.93	49.88
10+	8.25	13.22	10.85
Spending on mobile (CFA, monthly)			
< 500	0.67	0.00	0.67
500 - 1,000	1.33	0.00	1.33
1,000 - 2,000	3.33	0.67	3.99
2,000 - 3,000	7.32	2.66	9.98
3,000 - 5,000	15.96	13.97	29.93
> 5,000	20.40	33.70	54.10
# Observations	221	230	451

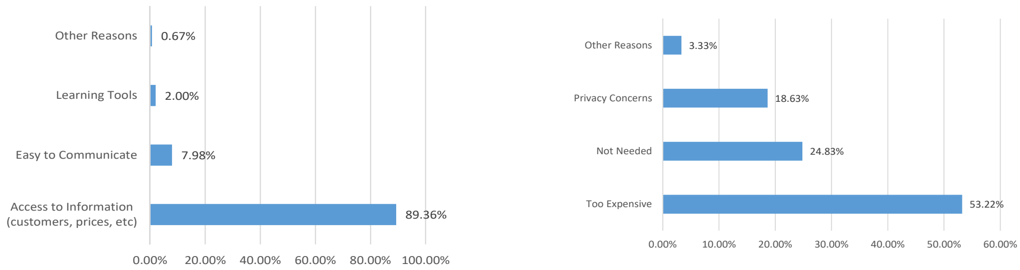
factors driving digital technology adoption, in line with the studies by Fageda et al. (2014), Urama and Ogbu (2018), Whitacre et al. (2015), among others.

These features and patterns of grains and legumes value chains in Benin provide empirical relevance for designing a tractable structural model of technology adoption which is discussed in the next section.

3 Theoretical Framework

In this section, we develop a simple model that attempts to formalize the micro foundations of technology adoption among small scale food suppliers, rather than a general

Figure 3: Reasons for Using (left) and Not Using (right) Digital Technologies



Source: Authors' survey and calculations

theory of digital technology adoption which would involve many other components that are not yet present in Benin or developing countries with similar technology features and socio-economic structure. We rely on the empirical evidence from the survey data on the grains and legumes markets in Benin to guide the design of our theoretical framework that facilitates intuition on the underlying behavior. The model is anchored in the observed digital technology adoption patterns, usage, and market frictions, and provides a tool to quantitatively analyze the implications of various policy options that could boost productivity and generate better economic outcomes (Bloom et al., 2012; Ndubuisi et al., 2022). One key observation about the occupational landscape is that we do not have any digital nomad in our population, as grains and legumes suppliers operate in markets at fixed locations.[5] In addition, usage costs and reliability concerns suggest that wealth-related credit constraints as well as quality of the broadband are are important market frictions to be accounted for in the modeling framework. The model discussed below delineates these key ingredients, relationships and channels. Let's stress that most of the previous studies on digital technology adoption in Africa focus on the farmers and producers side effects (Suri and Udry, 2022; Oliva et al., 2020; Magruder, 2018; Aker and Ksoll, 2016; Koundouri et al., 2006). Instead, this paper takes a different perspective by shifting the attention to the intermediaries (suppliers) who trade foods in agricultural value chains.

3.1 Model set up

Our simple estimable model of digital technology adoption among small scale grain and legumes suppliers assumes a continuum of heterogeneous agents who differ by their digital-specific productivity, and their initial wealth endowment that they may use as

[5] Digital nomads are location-independent people such as Youtubers and bloggers who use technology to work online in various locations rather than a fixed business location.

collateral to obtain credit. It elicits the economics of suppliers who own wholesale or retail shops, rent capital, employ people, and have to choose between incorporating digital technologies in their daily activities—namely, accessing mobile broadband and using digital mobile phone applications—and not using them. The agent's digital-specific productivity is denoted $\eta \in (0, \bar{\eta})$, where $\bar{\eta}$ is a finite upper bound, and their initial wealth or asset $z \in (0, +\infty)$ can be used as collateral to secure credit loans. Intuitively, the characteristic η can be interpreted as the agent's ability to exploit digital mobile applications to publicize, build networks, settle deals, and/or learn new skills that ultimately enable them to buy and sell their products more effectively.

Non-Adopters

The output, y_o, of a non-adopting or "old fashioned" business is the gross per-period margin (or value added) of the supplier firm, that is, the difference between the sales and the cost of goods sold (McAnally, 1963). Baily and Solow (2001) argue that this measure of retail output is both conceptually and empirically appealing. It is related to its input through a decreasing return to scale technology:

$$y_o = Ak^{\alpha}l^{\beta}$$

The production technology accounts for three main components: (i) a capital input, k, (ii) a labour input, l, which includes the total number of permanent and temporary workers, (iii) and the productivity factor in this traditional technology, A. It is noteworthy to mention that while A is the productivity of a non-adopter, it also reflects the baseline productivity for an adopter who can scale it up by using digital technologies. In practice, k captures elements such as the establishment's selling area or the cost of energy storage, refrigeration equipment, lighting, shelving, and display equipment monitoring and equipment procurement and delivery (Nguimkeu, 2016). The parameters $\alpha \in (0, 1)$ and $\beta \in (0, 1)$ are the capital and labor shares of the production process. Following Lucas (1978), we assume that $0 < \beta + \alpha < 1$, which implies diminishing returns to scale in variable factors at the establishment level.

Consistent with our data and in line with several empirical studies in developing countries (e.g., Karaivanov, 2012; Karaivanov and Yindok, 2022; Nguimkeu, 2014; Paulson et al., 2006), we assume that capital is constrained among these suppliers. The maximum capital that an entrepreneur uses, $\bar{k}$, is a fraction of their initial asset endowment z. That is, $\bar{k} = \lambda z$, for some proportionality factor $\lambda \in (0, \infty)$.[6] Denote the gross interest rate by r, and the wage rate by w. The profit maximization program of a business owner who does not use digital technologies depends on their level of financial constraints and is given by:

[6]Under imperfect credit markets with limited liability, one can show that the maximum amount of capital that banks are willing to lend to firms is a proportion of the wealth that they use as collateral (see, e.g., Buera and Shin, 2013).

$$\pi_o(z) = \max_{k,l}\left\{Ak^\alpha l^\beta - rk - wl : 0 \le k \le \bar{k},\, l \ge 0\right\}$$
$$= \begin{cases} \pi_o^u := (1-\gamma)A^{\frac{1}{1-\gamma}}\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\gamma}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\gamma}}, & \text{if } z \ge z^*, \\ \pi_o^c := (1-\beta)A^{\frac{1}{1-\beta}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\beta}}\bar{k}^{\frac{\alpha}{1-\beta}} - r\bar{k}, & \text{if } z < z^*, \end{cases} \tag{1}$$

where π_o^u and π_o^c are the financially unconstrained (u) and constrained (c) maximum profit, $\gamma = \alpha + \beta$, and $z^* = \frac{1}{\lambda}A^{\frac{1}{1-\gamma}}\left(\frac{\alpha}{r}\right)^{\frac{1-\beta}{1-\gamma}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\gamma}}$ is the minimum collateral needed to operate a financially unconstrained business.

Adopters

A business owner with digital-specific productivity, $\eta \in (0, \bar{\eta})$, may decide to adopt digital technologies to improve the efficiency of their business activities. Specifically, using these digital technologies may boost the efficiency units of l units of hired labor to ηl. Accordingly, the production function of a digital technology adopter is given by:

$$y_d = Ak^\alpha(\eta l)^\beta.$$

where y_d is the gross per-period margin (or value added) of the supplier firm that uses digital technologies. The technical coefficient η can therefore be regarded as the relative difference in labor productivity between businesses that adopt these digital technologies and those that do not (e.g., Galor and Tsiddon, 1997).[7] There is, however, an entry cost to the usage of digital technologies as well as variable costs, all of which are accounted for as a per-period total amount of c in capital units.[8] These costs include *inter alia* the purchase and installation costs of devices (e.g., cable modem, digital subscriber line), mobile broadband internet subscription fees, and per-period service charges. We also assume that relying on mobile broadband services and adopting digital technologies for business activities involves a risk of losing output that occurs with a probability $p \in (0, 1)$. We incorporate this probability in the profit function of an adopter's business as a discount factor on output. This probability of output loss captures the concerns expressed by digital technologies users in our data and it increases as the quality of the mobile broadband connectivity degrades, network reliability issues (such as small bandwidth, and low-speed) increase, and data privacy and cybersecurity threats (such as the occurrence of fraud, manipulation, and deception) become more pervasive. Our data as well as evidence from neighboring countries such as Niger (Aker, 2010) and Nigeria (Urama and Ogbu, 2018) suggest that these digital technology related concerns may be quite substantial.

[7] Notice that η could also directly conflate the total productivity factor A without changing the model's main implications

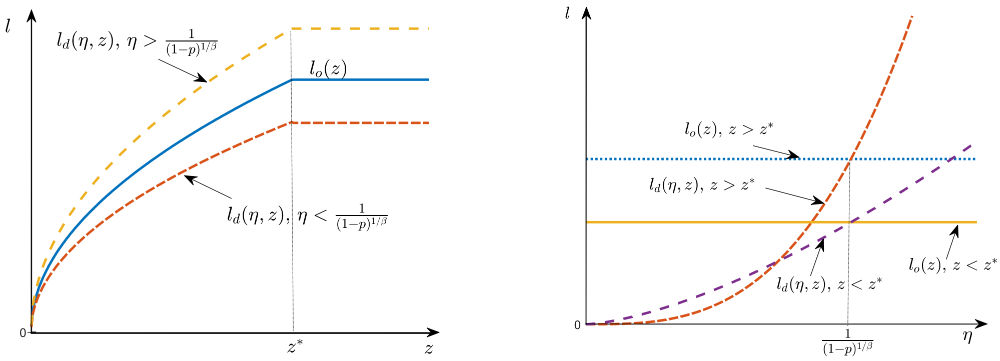
[8] Assuming a firm with infinite life, an entry fixed cost of c can be dispatched in per-period amounts of rc, given that $c = \sum_{t=0}^{\infty} rc/(1+r)^t$.

The maximum profit of an entrepreneur that uses digital technologies is

$$\pi_d(\eta, z) = \max_{l,k} \left\{ (1-p)Ak^{\alpha}(\eta l)^{\beta} - wl - rk - rc : \; 0 \le k \le \bar{k}, \, l \ge 0 \right\}$$
$$= \begin{cases} \pi_d^u := (1-\gamma)\left((1-p)\eta^{\beta}A\right)^{\frac{1}{1-\gamma}} \left(\dfrac{\alpha}{r}\right)^{\frac{\alpha}{1-\gamma}} \left(\dfrac{\beta}{w}\right)^{\frac{\beta}{1-\gamma}} - rc, & \text{if } z \ge z^*, \\ \pi_d^c := (1-\beta)\left((1-p)\eta^{\beta}A\right)^{\frac{1}{1-\beta}} \left(\dfrac{\beta}{w}\right)^{\frac{\beta}{1-\beta}} \bar{k}^{\frac{\alpha}{1-\beta}} - r\bar{k} - rc, & \text{if } z < z^*, \end{cases} \tag{2}$$

The corresponding labor demand for digital technology adopters, l_d, and labor demand for non-adopters, l_o, are such that for any level of wages w, the former is increasing in the digital-specific productivity, η. Thus, adopters with sufficiently high digital skills tend to hire more labor ($l_d(\eta, z), \; \eta > (1-p)^{-1/\beta}$) than their counterparts with relatively lower digital skills ($l_d(\eta, z), \; \eta < (1-p)^{-1/\beta}$) and non-adopters ($l_o(z)$), regardless of their wealth, z (Figure 4, left panel). The maximization results also show that an improvement in the quality and safety of the mobile broadband and related digital applications, reflected in a decrease in the probability of output loss p for digital technology adopters, narrows the labor demand wedge among all suppliers (non-adopters and adopters) as it allows a higher proportion of suppliers to adopt digital technologies. Moreover, among adopters, the labor productivity is higher for financially unconstrained suppliers ($z \ge z^*$) than constrained suppliers ($z < z^*$) as shown in the right panel of Figure 4.

Figure 4: Labor demand as function of digital skills and assets



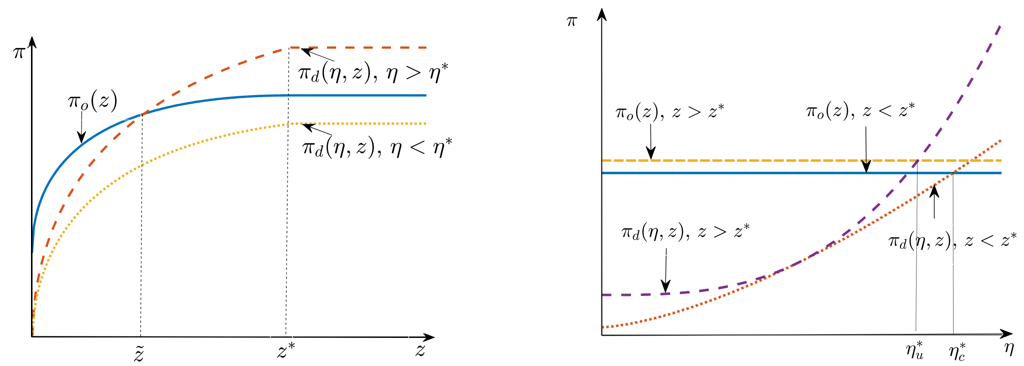
3.2 Adoption Decision

We now characterize how business owners make their decision to adopt digital technologies. We start by describing the information set of the grains and legumes suppliers in this economy. Suppliers know their personal attributes η and z, the market characteristics r and w, their productivity with the traditional technology, A, and its distribution across the value chain, the costs of mobile broadband services access, c, as well as the quality and safety of their usage captured by the probability of output loss p. Based on these parameters, these suppliers form their expectaions on the potential gain from each decision. Namely, they choose to adopt digital technologies if and only if the expected profit from doing so exceeds that from not using them. Formally, this means

$$\Pi_d(\eta, z) \geq \Pi_o(\eta, z) \tag{3}$$

in expectations, with respect to the distribution of A. The payoff functions of alternative adoption choices are illustrated in Figure 5. The profits of adopters with sufficiently high digital skills ($\Pi_d(\eta, z)$, $\eta > \eta^*$) tend to exceed the profits of their counterparts with relatively lower digital skills ($\Pi_d(\eta, z)$, $\eta < \eta^*$), regardless of their wealth, z (Figure 5, left panel). By contrast, the profits of adopters with sufficiently high digital skills ($\Pi_d(\eta, z)$, $\eta > \eta^*$) is higher than the profits of non-adopters only if their wealth z exceeds a cutoff point $\tilde{z}$. This captures the presence of credit constraints in the adoption decision. When suppliers are extremely financially constrained, $0 < z < \tilde{z}$, suppliers are better-off not adopting digital technologies ($\Pi_o(z) > \Pi_d(\eta, z)$), regardless of their digital skills, η. When they meet the minimum collateral requirement while still being financially constrained, $\tilde{z} < z < z^*$, they are better off adopting if they have the minimum digital skills, although they could profit more with better access to credit.

Figure 5: Profits as functions of digital skills and initial assets



Turning to the right panel in Figure 5, we see that the profits of adopters are increasing in η, while non-adopters' profits are inelastic with respect to η. This implies a critical digital skills threshold, η^* defined by

$$\eta^* = \begin{cases} \eta_u^* := (1-p)^{-1/\beta} \left(1 + \dfrac{rc}{(1-\gamma) y_o^u}\right)^{(1-\gamma)/\beta}, & \text{if } z \geq z^*, \\ \eta_c^*(z) := (1-p)^{-1/\beta} \left(1 + \dfrac{rc}{(1-\beta) y_o^c(z)}\right)^{(1-\beta)/\beta}, & \text{if } z < z^*, \end{cases} \tag{4}$$

where y_o^u (respectively, $y_o^c(z)$) are the unconstrained (respectively, constrained) expected outputs of an entrepreneur with digital productivity η and wealth z had they decided to remain a non-adopter. Equation 4 shows that an agent's decision is characterized by a digital productivity cut-off point, η^*, that depends on whether or not they are financially constrained. Below this digital productivity threshold, a preferred option for the agent is to remain a non-adopter, as $\Pi_o(z) > \Pi_d(\eta, z)$.

The existence and uniqueness of the productivity threshold, η^*, characterizing the adoption decision of the agent follows from the continuity and monotonicity of the profit functions with respect to η (Intermediate Value Theorem). Consequently, all agents with $\eta \geq \eta^*$ become adopters whereas those with $\eta < \eta^*$ remain non-adopters. For financially constrained entrepreneurs, the productivity threshold, η^*, is a decreasing function of wealth z, denoted $\eta_c^*(z)$. By contrast for financially unconstrained entrepreneurs, this cut-off boils down to a threshold, η_u^*, that does not depend on their personal characteristics but only depends on the markets and the digital infrastructure attributes (c and p). The adoption decisions of the grains and legumes suppliers in the model are summarized in the following proposition.

Proposition 1. *Consider a business owner with characteristics* (η, z)*:*

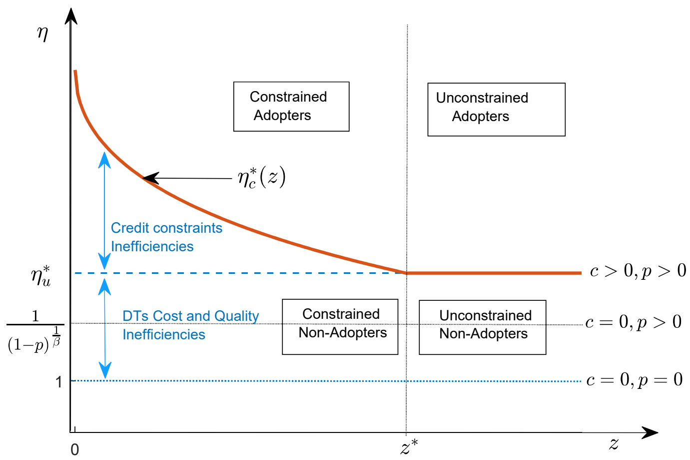
- *If* $\eta < \eta_u^*$*, then the business owner is a non-adopter.*
- *If* $\eta \geq \eta_u^*$*, then the business owner is an adopter only if* $z \geq z^*$*. However, if* $z < z^*$*, then the business owner is an adopter only if* $\eta > \eta_c^*(z)$*.*

where $\eta_c^*(z) > \eta_u^*$*, and* η_u^* *,* $\eta_c^*(z)$ *are the critical threshold defined in Equation (4).*

Proof. See Appendix B.1. □

The fact that $\eta_c^*(z) > \eta_u^*$ implies that financially constrained suppliers ($z < z^*$) need higher digital skills than their financially unconstrained counterparts for adoption to be a viable decision for them. Figure 6 illustrates the taxonomy of the digital technology adoption decision where four categories of suppliers emerge: financially constrained and unconstrained business owners, each of which can be adopters or non-adopters

Figure 6: Taxonomy of the selection to digital technology adoption



As depicted in Figure (6), if the economy had no financial constraints, zero cost of digital technologies adoption, and zero probability of output lost for adopters (e.g., reflecting a perfect quality and reliability of broadband connectivity), i.e., $\lambda = \infty$, $c = 0$, and $p = 0$, then any supplier with digital skills that can provide efficiency units of labor higher than 1, i.e. $\eta > 1$, would adopt. Thus, suppliers' digital skills would fully determine their decision to adopt digital technologies. Without financial constraints, the selection to adoption collapses to a simple comparison of η with η_u^* which only depends on the quality and cost of connectivity. However, in reality, markets frictions are usually non-trivial, leading to two sources of inefficiencies: inefficiencies due to credit constraints and inefficiencies due to cost and quality of digital technologies (Figure 6).

Implicit to this framework is the assumption that labor flows freely between business types and this mobility does not depends on employees personal characteristics (Meghir et al., 2015; Magnac, 1991; Pratap and Quintin, 2006; Fafchamps, 1993). This means that workers have no intrinsic preferences for the type of employer they work for and hence there is no labor displacement. Conversely, employers do not select workers based on their initial digital skills. This could be a strong, and possibly unrealistic, assumption if employment is highly susceptible to digital technologies (for example, in the case of employers that are pure digital nomads) or if there are low complementarities between digital skills and individual labor market characteristics. These are, however, not the situations we encountered in our context of grains and legumes value chains in the data. Moreover, as long as digital technologies entice some adopting firms to increase their demand for workers regardless of their digital skills, the main implications of our model would remain unchanged. It is also important to note that the nature of the selection to adoption as depicted in Figure 6 does not depend on the particular functional form of the production function specified. Any functional form for production that is increasing in digital skills at all levels of capital and labor and satisfies standard Inada conditions would yield similar behavior where four categories of suppliers emerge. This has implications for the possibility of non-parametric identification of our model based on any survey data where adoption status and its potential shifters are observed as well as any proxy for credit constraints at the respondent's level.

4 Reduced-Form Results

In this section, we undertake reduced-form regressions to substantiate our structural model framework and empirically test some hypotheses suggested by the descriptive statistics of the survey data. Our model and data suggest that personal characteristics such as wealth and digital skills affect digital technology adoption, which in turn affects the productivity of suppliers in the grains and legumes value chains. We first fit the probability of adoption and then estimate the effect of adoption on productivity.

4.1 The Probability of Adoption

We start by estimating the probability of adoption as a function of wealth, and other personal characteristics such as age, gender, education, experience, marital status, national origin, and membership to business association. To assess a supplier's wealth, we build a market value index of their household assets, using average prices from the Benin National Institute of Statistics. To minimize its endogeneity to adoption, we only used assets that were acquired more than 5 years ago (prior to 2017), that is, when the nationwide mobile broadband coverage in the country was still very low (less than 15% according to International Telecommunication Union, 2022).[9] We also examine how adoption is affected by respondent's geographical proximity to other adopters using an index of proximity (denoted $NearUsers$) that counts the number of adopters located within a 500-meter radius of the respondent's location. The probability of adoption is modeled as

$$\Pr[Adopt_i = 1|Z_i] = F(Z_i'\delta) \tag{5}$$

where Z_i is a vector of regressors. $F(\cdot)$ is a cumulative distribution function (CDF) taking the form of the uniform CDF for a linear probability model, or the standard normal CDF for a probit model.

Table 2 reports the linear probability and probit estimation results. The coefficient on $Wealth$ shows that the respondent's initial household wealth is positively and significantly associated with the probability of adoption in both the OLS and probit results. Thus, the wealthier the business owner the higher their likelihood to adopt. The choice of adopting digital technologies increases a supplier's prospects of earning higher profits, as predicted by our theoretical model. Interestingly, the wealth effect disappears when we run these regressions for respondents at the highest percentiles of the wealth distribution. This suggests, as also shown in our theoretical framework, that wealth becomes an irrelevant predictor of digital adoption beyond a certain threshold (See Table C1 in Appendix C). Similarly, the coefficient on $NearUsers$ is positively associated with adoption, implying that suppliers who are geographically closer to adopters are also more likely to adopt. This result is consistent with the findings in studies by Birke (2009), Fafchamps (2001), and Katz and Shapiro (1994), to name a few. Education is also positively and significantly associated with the probability of adoption, as suggested by our descriptive statistics (Aker and Mbiti, 2010; Suri and Udry, 2022). In contrast, the coefficient on Age is negative and significant, implying that younger entrepreneurs are more likely to adopt digital technologies than older ones (Jelfs and Richardson, 2013; Lee and Coughlin, 2015; Meyer, 2011). Our data do not show any significant effect of experience on the likelihood of adoption, and the coefficients on Female, Married, Native and Member (i.e. membership to business associations) are all non significant. This means that women and men, married and non-married persons, native and immigrants, and members and non-members of business associations are all equally likely to adopt

[9] These assets are household durable goods including television, radio, house, motorcycle, car, bike, and land.

Table 2: OLS and Probit Estimates of the Probability of Adoption

	(1) OLS	(2) Probit
Wealth	0.0142***	0.0417***
	(0.0047)	(0.0137)
NearUsers	0.0038***	0.0103***
	(0.0013)	(0.0039)
Age	-0.0077***	-0.0230***
	(0.0026)	(0.0078)
Female	0.0530	0.123
	(0.0597)	(0.180)
Education	0.0271***	0.0760***
	(0.0044)	(0.0133)
Experience	0.0577	0.1401
	(0.0716)	(0.214)
Married	0.0595	0.1210
	(0.0718)	(0.2130)
Native	-0.0338	-0.1170
	(0.0551)	(0.1590)
Member	0.0191	0.0643
	(0.0525)	(0.1580)
Observations	442	442
Adj/Pseudo R^2	0.169	0.148

Notes. Estimated average marginal effects. Standard errors in parentheses.
*p< 0.05, ** p<0.01, *** p<0.001

digital technologies, all else equal. These probability regressions also serve as a "first stage" for the instrumental variable estimation of the impact of adoption that we discuss in the next section.

4.2 Impact of Technology Adoption

One of the main implications of the theoretical model is that adopters are more productive and demand more labor than their non-adopters counterparts, and these outcomes are increasing in the level of assets. To test these hypotheses, we estimate a model of the form

$$Outcome_i = \beta_0 + \beta_1 Adopt_i + X_i'\gamma + u_i \tag{6}$$

where $Outcome_i$ is an outcome of interest. To measure productivity, we use the number of major monthly business transactions as the main outcome, where a 'major' business transaction is one that involves 5,000 CFA or more in sales.[10] This captures the productivity of an agrifood trading business since a high number of transactions implies a high frequency of business operations and is also associated with higher sales. One

[10]Suppliers typically recall larger trades that exceed 5,000 CFA.

could have used profits or profit rate as alternative outcome variables of interest. However, we could not compute suppliers' profits due to data limitations. We collected only scanty data on sales and were not able to record input costs because grains and legumes suppliers in Benin typically do not have a formal bookkeeping system. This trade remains predominately a subsistence activity in Benin and many suppliers often mix their personal and business expenses, which complicates the assessment of their profit margins.

Given that the adoption status is potentially endogeneous, we use the number of nearby users, $NearUsers$, as an instrument for the instrumental variable estimation of the impact of adoption. As found in our Probit and OLS results above, the number of nearby users significantly influences the probability that a respondent would adopt digital technologies. However, the number of nearby users is unlikely to affect a respondent's number of monthly business transactions, except through adoption. A potential weakness of this instrument is that some suppliers may receive relevant market information from nearby adopters and use it to perform additional transactions without adopting digital technologies. However, the exogeneity tests suggest that our instrument satisfies the exclusion-restriction criterion. This is because the additional business transactions are mainly operated through the KasuwaGo app, which is a digital trading platform for grains and legumes introduced earlier. Moreover, the structural estimation of our model discussed in Section 5 further safeguards against potential endogeneity issues. The vector X_i gathers individual characteristics such as initial wealth, age, education, gender, experience, marital status, and membership to business association. u_i is a conditionally mean-zero error term. Because the dependent variable is a count, Table 3 also report results from Poisson regressions, both ordinary and IV.

Table 3: The effect of adoption on business transactions

	Dependent Variable: Transactions			
	(1) OLS	(2) Poisson	(3) 2SLS	(4) IV Poisson
Adopt	2.2236**	2.2507***	4.3454**	4.5681***
	(0.8117)	(0.3652)	(2.1323)	(0.9649)
Other controls	Yes	Yes	Yes	Yes
Adj/Pseudo R^2	0.1120	0.1014	0.0899	–
# Observations	445	445	448	448

Notes. All estimates are average marginal effects. Standard errors in parentheses.

Significance codes: *p< 0.05, ** p<0.01, *** p<0.001. Other controls not reported in the table include Wealth, Age, Education, Experience, Female, Married, Native, Member, and the constant.

We focus our attention on the effect of adoption on the number of monthly business transactions. In all specifications, the effect of adoption is positive and significant, implying that adoption leads to a greater firm performance, as predicted by our theoretical model. The regression coefficients range from 2.22 for the OLS specification all the way to 4.56 for IV Poisson regression. This means that adopters perform on average 2 to 5 transactions more than non-adopters, everything else equal. Given that non-adopters perform on average 10 transactions per month, this suggests that digital technology adoption could lift the monthly frequency of trades by up to 50%. When we added $NearUsers$ among the regressors, the associated coefficient is not significant while all other statistics remained almost unchanged. This means that $NearUsers$ has no effect on the outcome once *Adopt* has been accounted for.[11]

We also examine heterogeneous effects across gender by interacting the treatment variable *Adopt* with the $Female$ dummy variable. This allows to estimate and compare effects across four groups of people: women adopters, women non-adopters, men adopters and men non-adopters. The adoption rates are 51.1% among women, and 48.8% among men in the data. The regression results are reported in Table 4. In this regression, the

Table 4: Heterogeneous effect of adoption on business transactions

	Dependent Variable: Transactions			
	(1)	(2)	(3)	(4)
	OLS	Poisson	2SLS	IV Poisson
Adopt	5.2736**	5.7015***	8.3605**	8.9158**
	(2.3161)	(0.7914)	(2.9726)	(4.3049)
$Female$	-0.6762	-0.0051	0.0906	0.2123
	(1.8653)	(0.6723)	(1.6327)	(0.4074)
Adopt × $Female$	-3.5928**	-4.1074**	-5.4415**	-5.8541**
	(1.3806)	(0.8391)	(2.2457)	(2.6092)
Other controls	Yes	Yes	Yes	Yes
Adj/Pseudo R^2	0.1350	0.1453	0.079	–
# Observations	445	445	448	448

Notes. All estimates are average marginal effects. Standard errors in parentheses.
Significance codes: *p< 0.1, **p<0.05, ***p<0.01. Other controls not reported in the table include Wealth, Age, Education, Experience, Married, Native, Member, and the constant.

coefficient on *Adopt* represents the treatment effect for men. It shows that men adopters perform on average 5.3 to 8.9 more transactions than men non-adopters, everything else equal. This gap is about twice bigger than the homogeneous treatment effect obtained earlier. The coefficient on $Female$ is insignificant across all specifications, showing that there is no significant difference in performance between women non-adopters and men non-adopters. The average difference between women adopters and women non-adopters is obtained by summing up the coefficients on *Adopt* and *Adopt* × $Female$. This effect is therefore estimated at about 1.7 for OLS, 1.6 for Poisson, 2.9 for 2SLS, and 3.0 for IV

[11] This result together with other formal tests confirm that the number of nearby adopters satisfies the exclusion-restriction condition.

Poisson. Thus women adopters perform on average 1.6 to 3.0 more transactions than their non-adopters counterparts. The difference between the effect of adoption on men and on women is large and significant. It varies between 3.6 to 5.8 across specifications (see the coefficients for $Adopt \times Female$ in Table 4). This means that while women adopt more as we found in our descriptive statistics, men tend to benefit more from these technologies. A plausible explanation could be that women spend disproportionately more of their online time dealing with other issues beyond their business activities compared to men, including, e.g., household purchases, children educational contents, among others. More information would be needed to better understand the underpinnings of this heterogeneity. These reduced-form results validate some of our theoretical predictions and suggest some functional relationships that we will explore in the structural estimation.

5 Structural Estimates and Policy Evaluation

We now derive the likelihood function of the model and use it to estimate its structural parameters. This allows to further assess how our conceptual framework rationalizes the data collected on mobile technology adoption in the grains and legume value chains in Benin. These structural estimates are then used to evaluate the effects of various counterfactual policies.

5.1 Structural Estimation and Model Fit

We estimate the model by constructing a likelihood function that matches the probability of adoption and output from the model with the corresponding adoption status and business transactions in the data. Identification consists in uniquely identifying the joint distribution of unobservable digital skills and entrepreneurial talent to their underlying structure in the model.

Likelihood Function

We denote by $Adopt_i$ the adoption status of supplier i observed in the data. The model predict that

$$Adopt_i = \mathbf{1}[\pi_{d,i}(\eta_i, z_i) \geq \pi_{o,i}(z_i)] = \mathbf{1}[\eta_i \geq \eta_i^*]$$

where η_i^* is given by Equation (4) and depends on the supplier's wealth z_i, the cost of adoption c_i taken as the monthly amount spent on internet connectivity, and the institutional parameter p which reflects the risk of digital technology adopters losing their output. To estimate the structural model, we assume that digital skills are log-normally distributed among individuals conditional on their education $Educ_i$, age Age_i, and proximity with broadband internet users $NearUsers_i$. These conditioning variables are suggested by our reduced-form results and the last factor captures network effects that can shape a supplier's skill and adoption of digital technology (Birke, 2009; Fafchamps, 2001; Jackson et al., 2017; Katz and Shapiro, 1994). Formally, we specify the distribution of digital skills as follows

$$\ln \eta_i = \kappa_0 + \kappa_1 Educ_i + \kappa_2 Age_i + \kappa_3 NearUsers_i + \varepsilon_i \tag{7}$$

where $\varepsilon_i \sim N(0, 1)$. We assume a log-normal productivity for the supplier under the traditional technology, and set its expectation to 1, $E(A_i) = 1$, for simplicity. This means that coefficients obtained from Equation (7) can be viewed as deviations from their initial (traditional technology) levels when the supplier adopts digital technologies.

Let $\bar{\eta}_i = \kappa_0 + \kappa_1 Educ_i + \kappa_2 Age_i + \kappa_3 NearUsers_i$ be the conditional mean of the log digital skills for respondent i, and $X_i = [Adopt_i, Educ_i, Age_i, NearUsers_i, z_i, c_i]$ denote a vector of observables including both those driving digital skills as well as those associated with the decision factors.[12] The vector of structural parameters $\boldsymbol{\psi} = (\kappa_0, \kappa_1, \kappa_2, \kappa_3, \alpha, \beta, \lambda)$ includes average baseline digital skills κ_0, the conditional correlations of digital skills with education κ_1, age κ_2, and the network effect of nearby digital users κ_3. It also includes the elasticities of capital and labor in the production process α and β, as well as the proportion of wealth that can be invested λ.

The building blocks of the log-likelihood function are written below. The joint probability of firm i's observed adoption and output is given by

$$f(y_i, Adopt_i = 1 | X_i, \boldsymbol{\psi}) = f(y_i | Adopt_i = 1, X_i, \boldsymbol{\psi}) \Pr[Adopt_i = 1 | X_i, \boldsymbol{\psi}], \tag{8}$$

whereas the joint probability of firm i's observed non-adoption and output is

$$f(y_i, Adopt_i = 0 | X_i, \boldsymbol{\psi}) = f(y_i | Adopt_i = 0, X_i, \boldsymbol{\psi}) \left(1 - \Pr[Adopt_i = 1 | X_i, \boldsymbol{\psi}]\right). \tag{9}$$

The probabilities of observing adoption, $\Pr[Adopt_i = 1 | X_i, \boldsymbol{\psi}]$, the probability of observing output y_i given adoption, $f(y_i | Adopt_i = 1, X_i, \boldsymbol{\psi})$, and the probability of observing output y_i given non-adoption, $f(y_i | Adopt_i = 0, X_i, \boldsymbol{\psi})$, are derived from the structural model as described in detail in Appendix B.2. Combining these probabilities yields the following log-likelihood function for the structural model:

$$\mathcal{L}_i(\boldsymbol{\psi}) = \sum_{i=1}^{n} \left\{ Adopt_i \times \ln f(y_i, Adopt_i = 1 | X_i, \boldsymbol{\psi}) + (1 - Adopt_i) \times \ln f(y_i, Adopt_i = 0 | X_i, \boldsymbol{\psi}) \right\} \tag{10}$$

where the components of this function are given in Appendix B.2.

Institutional Parameters

To run the estimation, we need to set the values for the gross interest rate r and the probability p of output loss by digital technology adopters. The gross interest rate is fixed at $r = 1.053$ which corresponds to its official average monthly market rate (World Bank, 2016), and the wage rate is set at the official minimum monthly wage of $w = 30,000$ CFA Francs in Benin (INStaD, 2016). We construct the discount factor $1-p$ as an index of reliability of the broadband internet, where $1-p$ is the joint probability of quality—proxied by the penetration or coverage rate—and safety—proxied by the proportion of

[12] The other observables z_i and c_i enter the structural estimation in way that is explained in Appendix B.2.

respondents who did not report privacy concerns:

$$p = 1 - Cover \times Safe.$$

According to the International Telecommunication Union (2022) estimates, the penetration rate of broadband internet in Benin was 42% in 2022 (i.e., the year prior the year of the survey), and the proportion of respondents that did not report privacy concerns was 95.6%. This implies a discount factor of $1 - p = 40.3\%$.

Identification

Since this is a maximum likelihood estimation with a fully tractable model, parameter identification can readily be inferred from the non-singularity of the corresponding information matrix (Rothenberg, 1971). Alternatively, the identification of the model parameters can also be understood through the lens of the log-normal Roy model as discussed by Heckman and Honoré (1990). It involves, four sets of key variables. First, Education and Age help identify the log digital skill parameters by shifting its mean. Second, the exclusion restriction between business types is driven by the number of adopters in the neighborhood, which shifts the productivity of the supplier only if they are adopter of digital technologies. Third, variations in the labor and capital shares come from the shifts in output, wealth and individual costs. Fourth, the heterogeneity in initial wealth is what allows to pin down the credit constraint parameter.

Results

The structural estimates are obtained by maximizing the likelihood function given by Equation (10), using numerical algorithms as described in Appendix B.2. The maximum likelihood estimation results are presented in Table 5.

The correlation between digital skills and education, κ_1, is estimated at 0.103, implying that any additional unit of education is associated with a 10.3 percent increase in digital skills. This suggests that education may be a relevant driver of digital technology adoption in Benin. The correlation between digital skills and age, κ_2, is estimated at -0.155, implying that any additional year of age is associated with a 15.5 percent decrease in digital skills. This suggests that older suppliers are less likely to adopt than younger ones. The correlation between digital skills and the number of users in a 500-meter radius, κ_3, is estimated at 0.0034, implying that any additional user in this radius is associated with a 0.34 percent increase in digital skills. This suggests that digital skills can be learned or instilled by others around us. The degree of credit constraints, λ is estimated at 5.5 implying that total investment is bounded to up to 5.5 times the value of initial wealth. The implication for borrowing constraints should, however, be understood with caution. It does not necessarily mean that suppliers can borrow up to 5.5 times the value of their wealth in a financial institution. In the data, suppliers claimed that about 70% of the total initial business investment came from personal savings, gifts, family transfers and remittances, etc. Loans from commercial banks and other financial institutions represented the remaining 30%. The estimated multiplier should be discounted by about 30% to get a better sense of the degree of credit constraints in the formal credit

Table 5: Structural MLE Estimates of the Model

Parameter	Name	Estimate	Std. Error
Log Digital Skills			
Constant	κ_0	3.4419	0.4551
Education	κ_1	0.1031	0.0137
Age	κ_2	-0.1551	0.0206
NearUsers	κ_3	0.0034	0.0012
Production and Constraint			
Capital share	α	0.1426	0.0368
Labor share	β	0.8377	0.3565
Wealth	λ	5.5013	0.0177
Log-Likelihood		-102.42	
Observations		451	

Notes. Standard errors are calculated using bootstrap samples.

market, that is, about 1.65. The estimates of α and β mean that a percent increase in the capital of the business is associated with a 0.14 percent increase in output, while a percent increase in hired labor increases output by 0.84 percent, respectively. The sum of these two elasticities of input factors is close to 1, suggesting that the supply of grains and legumes might be a very competitive market. These structural results can be tied to the reduced-form estimates obtained earlier (see Tables 2 and 3) and, together, they provide empirical evidence from the grains and legumes value chains in Benin that are consistent with the main implications of our conceptual model.

Model Fit

Before turning to model simulations, we first assess the fit of our model. We considered other specifications for the distribution of skills (available from the authors), especially one where wealth was added as a covariate for log digital skills. The corresponding correlation estimate was statistically insignificant, implying that our measure of initial wealth is not acting as a proxy to digital skills. These alternative specifications gave worse model fits (i.e. lower log-likelihood values) than the one reported above. As shown in Table C2 (Appendix C), our estimated structural model does well predicting some simple observations in the data. For example, our structural model predicts that 49.8% of suppliers are digital technologies adopters, and our observed data shows a 50.6% adoption rate. Our model also predicts that average number of monthly transactions is 11.2, with 13.6 for adopters and 10.01 for non-adopters on average. In the observed data these numbers are 11.6 for the whole sample, with 13.05 for adopters and 10.09 for non-adopters on average. We also compare reduced-form treatment effects estimated from the observed data and those from the model generated simulated outcomes. Our structural model predicts a treatment effect of 4.15, while the reduced-form treatment effect is estimated at 4.35 for our 2SLS specification in Table 3. In other words, all of the magnitudes and signs on estimates from observed behavior are well matched by model estimates. In particular, none of the deviations between the data and the structural model (percent error rate) for the observed statistics exceeds 5% (see, last column of Table C2, Appendix C).

5.2 Policy Evaluations

Previous studies by Aker (2010), Conley and Udry (2010), Gollin and Udry (2021), Suri and Udry (2022) suggest that digital technology adoption can help mitigate some inefficiencies in the agricultural value chains in Sub-Saharan Africa. Barriers to digital technology adoption such as high service costs and poor quality of broadband internet connections may have contributed to a sizeable misallocation of skills and resources in the agriculture sector. Using our estimated model, we run a set of counterfactual simulations to evaluate the impact of policy changes on digital technology adoption as well as the associated productivity gains in the grains and legumes markets in Benin. We consider three policy options: (1) improving quality of connectivity, (2) lowering broadband internet service costs, and (3) increasing access to credit. These policies are evaluated relative to the current state implied by the estimated model. The new counterfactual outcomes (fraction of adopters, aggregate output, etc.) are obtained as a result of changes in policy parameters, assuming that wage and interest rates as well as the distribution of wealth are fixed. These counterfactual results should therefore be regarded as short-term projected outcomes.

Improving the quality of connectivity

We assess the implications of a policy change which would enhance the quality of the broadband internet. This can be achieved in our framework by broadening the internet coverage, or upgrading the safety of the broadband network, or both (Aker and Mbiti, 2010; Beaman et al., 2023; International Telecommunication Union, 2022).[13] This counterfactual policy change, which makes the broadband internet more reliable, would imply a lower probability of output loss related to digital technology adoption. We formalize it as

$$\tilde{p} = p - \tau_p, \qquad 0 < \tau_p < p,$$

where τ_p is the increment in quality and $\tilde{p}$ is the new probability of output loss.

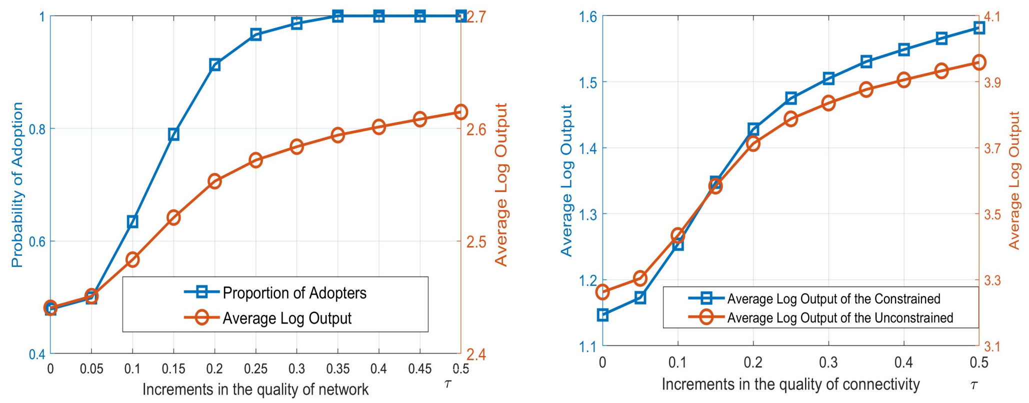
We evaluate the impact of this downward shift in the probability of digital output loss along four dimensions. The left panel of Figure 7 shows the impacts of this counterfactual policy change on the adoption rate (share of adopters over total market participants)

[13] The quality of the broadband internet can also be improved by reducing the latency of the network for high-speed connections, deploying the latest fiber optic technologies to minimize electronic interferences, and fostering competition among broadband internet providers (Fageda et al., 2014; Ndubuisi et al., 2022).

and the average of (log) output for all suppliers (both adopters and non-adopters). Note that this left panel figure has 2 vertical axes: the scale of the left hand side y-axis is a probability ranging from 0 to 1 whereas the scale on the right is in log points which implies that changes are in percent. First, we see that the share of adopters increases markedly, reaching almost 100 percent for a 35-percentage point decrement in the probability p. This reflects the impact of the improved broadband quality on the probability of adoption or adoption rate, that is, the extensive margin of digital adoption (D'Andrea and Limodio, 2023; Hjort and Poulsen, 2019). Following Kumar et al. (2023), Bennouna et al. (2024) estimate that the investment costs of extending 4G internet coverage to the entire population could amount to 2.5% of Benin's projected average annual GDP between 2021 and 2030. Second, the response of the average (log) output to the policy change suggests a 2-speed increase, reflecting both the extensive and intensive margins of digital adoption. When the decrement in the probability of output loss due to digital adoption is less than 35 percentage points, i.e. $\tau_p < 0.35$, we see a rapid increase in log output mainly reflecting the effect of better quality internet on the extensive margins. That is, average output increases because of new entrants. When $\tau_p \geq 0.35$, however, the adoption rate is close to 100 percent, and we see a slower increase in (log) output mainly reflecting the intensive margins. That is, average output increases because of improved efficiency among adopters.

The third and fourth dimensions are shown in the right panel in Figure 7, which illustrates the difference in log output response for constrained and unconstrained adopters. The range for unconstrained adopters is roughly 10 times as much as that of constrained ones. However, the constrained adopters seem to have higher elasticity (steeper slope) of output to connectivity improvement than unconstrained adopters.

Figure 7: Impact of Improved Quality of Connectivity



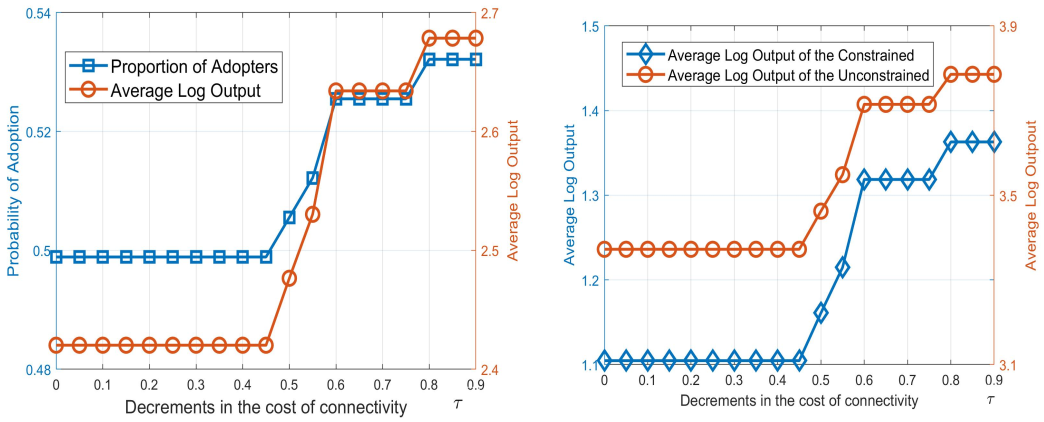
Reducing the costs of connectivity

We now turn to assessing the effects of a reduction in the broadband internet service costs by a fraction τ_c, such that the new cost is:

$$\tilde{c}_i = (1 - \tau_c) \times c_i, \qquad 0 < \tau_c < 1.$$

The left panel in Figure 8 shows a step-wise increase in the adoption rate (probability of adoption) and the log output, as connectivity costs are slashed. Actionable policies to reduce connectivity cost include subsidizing fiber optic national backbone infrastructure as currently happening in Uganda (Africa Telecom Review, 2024), exploiting the power of internet exchange points (IXPs) for advanced internet connectivity (African Union, 2020) and other policies (Fageda et al., 2014; International Telecommunication Union, 2022; Urama and Ogbu, 2018). The adoption rate remains virtually unchanged if the broadband cost reduction is less than 45 percent and then plateaus around 53 percent when the cost reduction reaches 90 percent. The log output follows a similar pattern, albeit on a larger scale. This step-wise increase after a decrement of 45 percent may reflect a nonlinear threshold beyond which broadband internet services become affordable to some non-adopters. It may also reflect the extent to which some non-adopters can substitute purchasing internet connection with other expenditures in their consumption basket. The elasticity of constrained adopters' log output to connectivity cost reduction seems higher (steeper slope) than that of unconstrained adopters. The fact that we are unable to entice everyone to adopt despite reducing the cost of internet all the way to zero is consistent with the observation that in the data, a sizeable fraction of suppliers (25%) reported not being interested in adopting digital technologies, regardless of their cost.

Figure 8: Impact of Reduced Cost of Connectivity



Improving access to credit

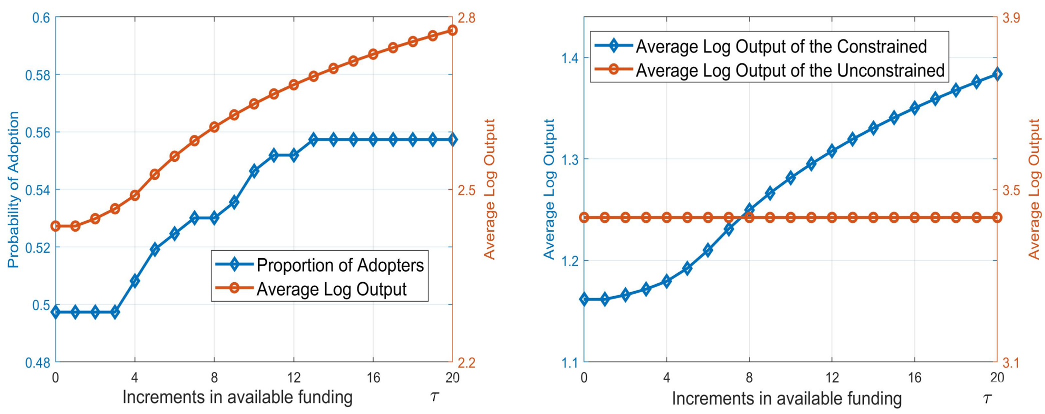
We also explore the model implications for digital technology adoption and output of a counterfactual policy which aims at facilitating the grains and legumes suppliers' access to credit. A number of studies have argued that credit constraints can impede the adoption of improved technologies among african farmers, including digital technologies

(Foster and Rosenzweig, 2010; Giné and Yang, 2009; Oliva et al., 2020). We assess a credit access policy by assuming that additional funding—a multiple of the average household wealth in the data— can be made available for suppliers to borrow. This implies the folowing adjustment on their budget limit:

$$\tilde{k}_i = \max\{\bar{k}_i, z_i + \tau_z \bar{z}\}, \qquad 0 < \tau_z < \infty,$$

where τ_z is a scaling factor and $\bar{z}$ is the average household wealth. Improving access to credit is inherently expected to affect constrained suppliers (Karaivanov, 2012; Karaivanov and Townsend, 2014; Nguimkeu, 2016). Looking at the left panel of Figure 9, we see that the probability of adoption increases gradually, driven by constrained adopters, from 50% up to 56% when $3 < \tau_z \leq 13$; it then plateaus when $\tau_z > 13$. This suggests that the maximum adoption rate is 56% irrespective of the amount of top-up funding available for suppliers to borrow. The average (log) output grows monotonically, mainly reflecting the output gains of constrained suppliers as they are able to borrow more. This is apparent in the right panel of Figure 9, where the (log) average output of constrained suppliers rises steadily as their access to credit improves whereas it remains flat for financially unconstrained suppliers. The inelastic response of the unconstrained suppliers' output is intuitive because they do not "need" additional credit to decide whether or not to adopt digital technologies. Among these unconstrained suppliers, the skilled (respectively, unskilled) ones are expected (respectively, not) to adopt digital technologies as accessing credit become easier.

Figure 9: Impact of Improved Access to Credit



The analysis of the implications of each of the three policy scenarios considered suggests that upgrading the quality of internet could deliver the largest digital adoption rate and output in our context, in line with recent empirical evidence by Elliott et al. (2024). However, these policy changes could be bundled to obtain better outcomes. A two-pronged policy mix which enhances the quality of internet connectivity and substantially reduces the associated service costs would entail sizeable mutually reinforcing effects on digital technology adoption and boost output gains. Likewise, a policy package which improves the quality of the broadband internet and facilitates the access to credit, especially for financially constrained suppliers, is expected to yield higher digital adoption rates and output. A policy mix combining lower connectivity costs with easier access to credit would yield better outcomes than implementing each policy separately, although the reinforcing effects would be weaker than the outcomes from the two-pronged policy packages discussed earlier. A three-pronged policy bundle to achieve better internet quality, lower internet service costs, and better access to credit is expected to deliver the largest beneficial outcomes.

6 Conclusion

This paper analyzes the determinants and outcomes of digital technology adoption in the subsistence food sector. We focus on small scale suppliers of grains and legumes in Benin using individual-level survey data collected in two semi-rural markets. We employ a stratified random sampling strategy to gather granular data on the suppliers' digital technology adoption and usage, individual characteristics, and business output. These suppliers are predominately women (80%), aged 45.8 on average with more than a decade of trading experience, and half of them employ 6 to 9 people. The digital technology adoption rate among suppliers is about 51% and one third of suppliers use their phones to trade products and/or settle business transactions. However, over half (52%) of them didn't have any formal education and are likely to learn about these technologies only through their neighbor users, while 25% are not interested in using digital technologies.

To rationalize the observed features and patterns in the data, we build a structural partial equilibrium model featuring a continuum of suppliers characterized by their digital-specific productivity, initial wealth that they can use as collateral in the credit market, and who face broadband connectivity costs and quality constraints. A supplier's digital-specific productivity enables them to use digital technologies to market and trade products more efficiently. The adoption decision is determined by a double partition of the profit function with respect to critical thresholds for digital productivity and wealth levels. A Supplier does not adopt digital technologies if their digital-specific productivity is lower than the critical cut-off. When this productivity exceeds the critical threshold, they adopt digital technologies only if their initial wealth is not constrained. In contrast, financially constrained suppliers face a higher critical digital productivity threshold than their financially unconstrained counterparts when choosing to adopt digital technologies.

To test the model implications with the collected data, we run both reduced-form and structural estimations. Our reduced-form estimates suggest that the probability of adoption increases in wealth, the number of nearby digital technology users, and education, but decreases in age because younger suppliers are more likely to adopt digital technologies than older ones. Adopters are estimated to perform on average 2 to 5 digital transactions more than non-adopters every month, up 50% increase, and this effect is higher for men compared to women. Using a maximum likelihood approach and a Roy-type identification strategy, we estimate the structural parameters of the model and found values that are consistent with the observed data and the reduced-form results. These estimates allow us to draw the model implications of three counterfactual policies: improved internet quality, reduced internet service costs, and easier access to credit. Of these three policy simulations, upgrading the internet quality implies the highest probability of digital technology adoption among suppliers and the largest output gains. We also find that multi-pronged policy packages yield mutually reinforcing positive adoption effects and production outcomes.

To the best of our knowledge, the structural test of the role of digital technology adoption, digital skills, and credit constraints in explaining the productivity of agricultural food intermediaries (suppliers) is new to the literature. Our results provide new insights to the growing literature on digital technology adoption among subsistence workers in Africa and complement those that relate to agricultural activities in developing countries. There are however some limitations as well as directions in which this research can be improved or extended. First, digital nomads are not included in our framework. While this type of businesses are not present in our data, it is becoming increasingly prevalent in African countries and should be integrated in future studies and relevant contexts. Second, because agents' behavior on the food demand side (i.e., consumers or other retailers) is absent from this analysis, the model does not allow to derive a general equilibrium solution through which digital technology adoption and related outcomes can be fully quantified over the rest of the economy. Hence, our simulation exercise does not capture aggregate welfare gains and does not allow to perform a cost-benefit analysis of the suggested policies. These important considerations are left for future research.

APPENDIX

A Details on data collection

A.1 Survey Design

Prior to starting the survey, we met with the managers of the targeted markets, government officials, and leaders of merchant associations to notify them beforehand of the survey objectives and timelines and build a representative list of potential respondents. A pilot survey was carried out in Bohicon and Ouando markets (our strata) in January 2023. The survey was later administered to grains and legumes suppliers in these markets between May and July 2023. A random sample of participants was drawn from the list of potential respondents in each market using a stratified sampling, and interviews were scheduled outside of the main market days. The grains and legumes market in Bohicon takes place on Wednesdays and Sundays whereas the Ouando market takes place every Tuesday, Thursday, and Saturday. To incentivize the participants to complete the survey interviews, airtime vouchers of 500 CFA Francs were offered to respondents upon completion of the questionnaire. Participants who withdrew from the survey at the last minute were replaced by other interviewees randomly drawn from the potential pool of respondents. Of the list of respondents, we focus on 451 grains and legumes suppliers that were successfully interviewed in Bohicon and Ouando markets after several attempts.

A.2 Challenges

Our biggest challenge was the difficulty in pinning down respondents. These are grains and legumes suppliers who typically can be interviewed in their shops on market days, when they are rather busy with customers and cannot devote much time to answer questionnaires. The majority of these suppliers also move frequently across markets and towns, which further complicates the interview scheduling process. In Ouando market, suppliers were very reluctant to participate to the survey. Many potential participants were concerned that the survey could be used by authorities to raise more taxes. They also complained that the government recently displaced merchants to rebuild the market, which disrupted their business activities. The enumerators were sometimes turned away, despite our continued engagement with the market officials before and during the survey to raise awareness. By contrast, data collection in Bohicon market was relatively easier. It took an average of three attempts in a span of two months to get a respondent to fully complete the questionnaire.

B Proofs

B.1 Proof of Proposition 1

The expected profit of the non-adopter and adopter are respectively

$$\pi_o(z) = \begin{cases} (1-\gamma)y_o^u, & \text{if } z \geq z^* \\ (1-\beta)y_o^c - r\lambda z, & \text{if } z < z^* \end{cases}, \quad \pi_d(z) = \begin{cases} (1-\gamma)[(1-p)\eta^\beta]^{\frac{1}{1-\gamma}} y_o^u - rc, & \text{if } z \geq z^* \\ (1-\beta)[(1-p)\eta^\beta]^{\frac{1}{1-\beta}} y_o^c - r\lambda z - rc, & \text{if } z < z^* \end{cases},$$

where y_o^u and y_o^c are the expected financially unconstrained and constrained outputs for non-adopters, given by

$$y_o^u = E_A\left[A^{1/(1-\gamma)}\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\gamma}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\gamma}}\right] \text{ and } y_o^c = E_A\left[A^{1/(1-\beta)}\left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\beta}}(\lambda z)^{\frac{\alpha}{1-\beta}}\right].$$

$E_A[\cdot]$ denotes expectation with respect to the distribution of the productivity of non-adopters, A.

Recall that $\gamma = \beta + \alpha$ and $0 < \gamma < 1$ under decreasing return to scale of output in input factors. If $z \geq z^*$, then $\pi_d(z) \geq \pi_o(z)$ is equivalent to $(1-\gamma)[(1-p)\eta^\beta]^{\frac{1}{1-\gamma}} y_o^u - rc \geq (1-\gamma)y_o^u$, which means that $\eta \geq (1-p)^{-1/\beta}\left[1 + \frac{rc}{(1-\gamma)y_o^u}\right]^{(1-\gamma)/\beta} = \eta_u^*$.

If $z < z^*$, then $\pi_d(z) \geq \pi_o(z)$ is equivalent to $(1-\beta)[(1-p)\eta^\beta]^{\frac{1}{1-\beta}} y_o^c - r\lambda z - rc \geq (1-\beta)y_o^c - r\lambda z$, which means that $\eta \geq (1-p)^{-1/\beta}\left[1 + \frac{rc}{(1-\beta)y_o^c}\right]^{(1-\beta)/\beta} = \eta_c^*$.

Since $1-\beta > 1-\gamma$ and $(1-\beta)y_o^c \leq (1-\gamma)y_o^u$, it must be the case that $\eta_c^* \geq \eta_u^*$.

B.2 Likelihood function

We drop the conditioning on X_i and ψ to simplify the notation. The individual log-likelihood function of an observation i is given by
$\mathcal{L}_i(\psi) = Adopt_i \times \ln f(y_i, Adopt_i = 1) + (1 - Adopt_i) \times \ln f(y_i, Adopt_i = 0)$,
where the joint probabilities can be rewritten as $f(y_i, Adopt_i = 1) = f(y_i|Adopt_i = 1)\Pr[Adopt_i = 1]$, and $f(y_i, Adopt_i = 0) = f(y_i|Adopt_i = 0)\Pr[Adopt_i = 0]$.

We now elicit each component of this log-likelihood function. As assumed earlier in Section 5, ε_i is a standard normal random variable and $\ln A_i$ is normally distributed, such that $E[A_i] = 1$. In what follows, the probability of being financially unconstrained is defined by

$$\Pr[z \geq z^*] = \Phi\left((1-\gamma)\ln z - c_3\right), \quad c_3 = (1-\beta)\ln\left(\tfrac{\alpha}{r}\right) + \beta\ln\left(\tfrac{\beta}{w}\right) - (1-\gamma)\ln\lambda.$$

The probability of observing output y for non-adopters is

$$f(y|Adopt = 0) = f(y|Adopt = 0, z \geq z^*)\Pr[z \geq z^*] + f(y|Adopt = 0, z < z^*)\Pr[z < z^*],$$

where

$$f(y|Adopt=0,z\geq z^*)=\phi\left((1-\gamma)\ln y-c_1\right),\quad c_1=\alpha\ln\left(\tfrac{\alpha}{r}\right)+\beta\ln\left(\tfrac{\beta}{w}\right),\quad \text{and}$$
$$f(y|Adopt=0,z<z^*)=\phi\left((1-\beta)\ln y-\alpha\ln z-c_2\right),\quad c_2=\alpha\ln\lambda+\beta\ln\left(\tfrac{\beta}{w}\right).$$

The probability of observing output y for adopters is

$$f(y|Adopt=1)=f(y|Adopt=1,z\geq z^*)\Pr[z\geq z^*]+f(y|Adopt=1,z<z^*)\Pr[z<z^*],$$

where

$$f(y|Adopt=1,z\geq z^*)=\phi\left(\frac{(1-\gamma)\ln y-c_1-\ln(1-p)-\beta\bar{\eta}_i}{1+\beta^2}\right),\quad \text{and}$$
$$f(y|Adopt=1,z<z^*)=\phi\left(\frac{(1-\beta)\ln y-\alpha\ln z-c_2-\ln(1-p)-\beta\bar{\eta}_i}{1+\beta^2}\right).$$

The probability of adoption is

$$\Pr[Adopt_i=1]=\Pr[Adopt=1|z\geq z^*]\Pr[z\geq z^*]+\Pr[Adopt=1|z<z^*]\Pr[z<z^*].$$

Here, we have:

$$\Pr[Adopt=1|z\geq z^*]=\Pr[-\varepsilon_i<\bar{\eta}_i-\ln\eta_u^*]=\Phi(\bar{\eta}_i-\ln\eta_u^*),$$

with

$$\ln\eta_u^*=-\frac{1}{\beta}\ln(1-p)+\frac{1-\gamma}{\beta}\ln\left(1+\frac{rc}{(1-\gamma)y_o^u}\right)\text{ and }y_o^u=e^{\frac{\gamma}{2(1-\gamma)^2}}\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\gamma}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\gamma}}.$$

Likewise,

$$\Pr[Adopt=1|z<z^*]=\Pr[-\varepsilon_i<\bar{\eta}_i-\ln\eta_c^*]=\Phi(\bar{\eta}_i-\ln\eta_c^*),$$

with

$$\ln\eta_c^*=-\frac{1}{\beta}\ln(1-p)+\frac{1-\beta}{\beta}\ln\left(1+\frac{rc}{(1-\beta)y_o^c}\right)\text{ and }y_o^c=e^{\frac{\gamma}{2(1-\gamma)^2}}\left(\frac{\beta}{w}\right)^{\frac{\beta}{1-\beta}}(\lambda z)^{\frac{\alpha}{1-\beta}}.$$

The actual maximization of the log-likelihood function, $\mathcal{L}_n(\boldsymbol{\psi})=\sum_{i=1}^n\mathcal{L}_i(\boldsymbol{\psi})$, is performed as follows. First, in order to ensure that a global maximum is reached we perform an extensive grid search over the seven parameters and we pick the parameter configuration which maximizes $\mathcal{L}_n(\boldsymbol{\psi})$. This parameter configuration is then taken as a vector of starting values for the actual optimization procedure. We solve the nonlinear optimization problem of maximizing $\mathcal{L}_n(\boldsymbol{\psi})$ by using the MATLAB routine *fminsearch* which represents a generalization of the polytope method using the Nelder-Mead simplex algorithm. This procedure has a high reliability, is relatively insensitive to initial values, and performs well with low-curvature objective functions (which if often the case in for log-likelihood functions). Finally, the standard errors for the estimated parameters are computed from the parameter variance-covariance matrix approximated with the sample second moment matrix of the estimated score vectors SS'/n, where S denotes the $n\times 7$ matrix of score vectors evaluated at the estimated parameters. These score vectors are obtained by differentiating $\mathcal{L}_n(\boldsymbol{\psi})$ with respect to the model parameters and evaluated at the estimated values.The standard errors of the estimated parameters are then the square roots of the main diagonal elements of the matrix SS'/n.

C Additional Tables

Table C1: OLS and Probit Estimates of the Probability of Adoption by Wealth strata

	(1) OLS	(2) Probit	(1) OLS	(2) Probit
Dependent variable: Adopt				
	Wealth<10.5		Wealth$\geq$ 10.5	
Wealth	0.0504***	0.046***	0.0171	0.0172
	(0.0108)	(0.0325)	(0.0116)	(0.0107)
NearUsers	0.0049***	0.0044***	0.0055**	0.0053**
	(0.0014)	(0.0013)	(0.0028)	(0.0025)
Age	-0.0082***	-0.0075***	-0.0030	-0.0043
	(0.0025)	(0.0025)	(0.0052)	(0.0054)
Educ	0.0222***	0.0219***	0.0312***	0.0299***
	(0.0049)	(0.0047)	(0.0096)	(0.0081)
Other Controls	Yes	Yes	Yes	Yes
Observations	340	340	108	108
Adj/Pseudo R^2	0.2181	0.1699	0.1729	0.1376

Notes. Estimated average marginal effects. Standard errors in parentheses.
*p< 0.1, ** p<0.05, *** p<0.01. Other controls not reported in the table
include Wealth, Age, Education, Experience, Married, Native, Member, and the constant.

Table C2: Observed Data versus Model Generated Estimates

Description	Data	Model	Deviation (%)
Adoption rate (%)	50.6	49.8	1.58
# Transactions—All	11.60	11.23	3.45
# Transactions—Adopters	13.05	13.61	4.21
# Transactions—Non-adopters	10.09	10.01	0.79
Treatment effect	4.35	4.16	4.36

Notes. The table reports averages. # Transactions are monthly counts of business transactions.
Deviation is the percent error rate obtained as $Deviation = \frac{|Model - Data|}{Data} \times 100\%$

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