The demand for advice: Theory and empirical evidence from farmers in Sub-Saharan Africa*

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Abstract

Low levels of investment into modern technologies, and limited use of measures that have low monetary cost but the potential for high yields, are often regarded as obstacles to further agricultural development. This paper investigates farmers' demand for one such measure, namely agricultural advisory services. These have modest (most frequently zero) monetary user cost but, according to some recent research, have the potential to result in large increases of yields. Yet, demand for these extension services is often low. We propose that costly attention may be part of the explanation for this. In our model, advisory services are available free of charge, but positive effects on production are only realized if farmers devote attention to listening to and implementing the provided advice. Modeling farmers as rational decision makers facing scarce attention, we identify the circumstances under which farmers may optimally abstain from demanding advisory services. The model complements the insights of other theories commonly used to explain sub-optimal farm decisions and outcomes, and generates testable predictions, which are consistent with empirical evidence based on a large farm-level panel dataset from Sub-Saharan Africa.

Keywords: economic development, advice, agricultural extension, rational inattention, Sub-Saharan Africa
JEL Codes: D91, O13, Q16

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1 Introduction

Increases in productivity are key to growth and poverty reduction, yet productivity in many domains is lacking far behind technological possibilities. This is particularly true for agricultural productivity in many parts of the developing world, especially in Sub-Saharan Africa (Jama and Pizarro, 2008; World Bank, 2008). One puzzling observation is that farmers do not make use of measures that have relatively low costs but are believed to offer high returns. In particular, modern farm inputs, such as fertilizer and improved seeds, have been demonstrated in a variety of contexts to have significant expected returns, yet are frequently not adopted and, conditional on adoption, inputs are used in suboptimal amounts. To help farmers overcome the underlying constraints, a major policy instrument used is the provision of agricultural extension and advisory services.[1]

A growing body of empirical evidence suggests that these services can have significant positive effects, including on farmers' management practices and adoption of better technologies (Cole and Fernando, 2013; Buehren et al., 2019), crop yields (Casaburi et al., 2014), profits (Bandiera et al., 2018), and poverty reduction (Dercon et al., 2009). Yet, demand for extension services is often low. In our dataset, which consists of nationally representative samples of farmers in three African countries, only 19% of farmers actively solicit agricultural advice (including from other farmers). The fairly low interest in agricultural advice despite the apparent potential for high returns is particularly puzzling in light of the low (most frequently zero) monetary user cost associated with receiving such advice.[2]

In this paper, we use a rational inattention model to argue that costly attention may be part of the explanation for this. Our model centers around the idea that farmers (like anybody else) face a limited capacity to attend to information, which causes attention to be a scarce resource.[3] Given that participation in extension programs is only worthwhile if farmers devote sufficient attention to listening to and implementing the provided advice, the decision to request extension services will depend on the amount of attention that farmers are willing to devote to their agricultural production process. Based on

[1] According to different sources, there are between half a million and one million agricultural extension workers worldwide, of which 90% are located in developing countries (Feder, 2005; Anderson and Feder, 2007).

[2] In our sample, 92% of respondents report having paid nothing for the advice that they received. Also note that the share of districts in which at least one farmer reports having received agricultural advice is 95% (84% of district-years), which suggests that extension services are widely available in the countries we study. This view is also in line with the findings of other studies. For example, surveying recent studies on extension services in Malawi, Ragasa (2018) report that three-quarters of Malawian farm households received agricultural advice in the last two years, and half of households received advice in the last 12 months.

[3] This feature is in line with a large body of psychological and experimental evidence on the limits of human cognition (DellaVigna, 2009; Caplin and Dean, 2013; World Bank, 2015), as well as a growing literature on the link between poverty and lack of mental resources (Banerjee and Mullainathan, 2008; Mani et al., 2013; Haushofer and Fehr, 2014).

this feature, we model household decision making in two domains, agriculture and non-agriculture, and identify the circumstances under which households will optimally abstain from demanding agricultural advice. In line with our theoretical results, we argue that considering costly attention as a binding constraint for farmers can contribute to a better understanding of the determinants of farmers' demand for advice.

One particular theoretical result, which is helpful in distinguishing the proposed channel from other theories commonly used in the literature to explain suboptimal farm decisions and outcomes, is that shocks in the non-agricultural domain may increase demand for agricultural advice. This prediction runs counter to much of the recent literature on psychology and poverty (e.g., Banerjee and Mullainathan, 2008; Haushofer and Fehr, 2014), according to which negative shocks in the non-agricultural domain would tend to absorb cognitive bandwidth, leading to less attention paid to agricultural production and thus less use of agricultural advice. The intuition is as follows. In the model, agricultural advisory services are available to farmers free of charge and farmers expect a positive effect on their production when participating in such programs. Absorbing advice and implementing the activities suggested by extension workers, however, requires attention, which is a costly resource as it can also be used to attend to decisions in other areas of the farmer's life (leading to expected utility gains in these domains). Shocks in the non-agricultural domain may raise the marginal utility of income, and consequently increase farmers' willingness to devote costly attention to the agricultural domain with the goal of generating additional income, thus increasing the probability that extension services are demanded.[4]

As an example, consider the following illustration. The household head is busy spending time with and thinking about a lot of things that he cannot avoid, but he would typically spend some of his time and attention on attending village meetings and discussing issues of village-level development. This is at the costs of being able to spend time on meeting the extension agent and spending some of his scarce attention on following up on what the extension agent tells him. Now some money is stolen or his house burns down. Now he is poorer and every dollar counts more. He hopes that spending time with the extension agent eventually provides additional dollars through better agricultural practices. Thus, instead of going to the village meeting and spending attentional resources on village-development issues, the household head now spends time and attention on meeting with the extension agent and following the received advice.

[4]Our model is based on rational inattention (Sims, 2003), which uses entropy to model costly attention. However, the prediction that non-agricultural shocks can lead to increased demand for agricultural advice arises independently of the specific structure of attention assumed in the rational inattention literature, and could therefore also be generated by a simpler model that is not based on entropy. As we discuss below, there are several advantages of using the rational inattention approach to model farmers' demand for advice.

Relying on detailed farm-level data on shocks (both related and not directly related to agriculture) and the use of extension services from Sub-Saharan Africa, we then demonstrate that empirical observations are consistent with the predictions of our model.[5] In particular, we show that there is statistically strong and robust evidence that, in line with the model, non-agricultural shocks are indeed associated with increased demand for extension. For this purpose, we split shocks into two categories, namely shocks that are directly related to agriculture (e.g., pest outbreaks and irregular rainfalls) and shocks that are not directly related to agriculture (e.g., shocks to farmers' wealth or health). In addition, our data allow us to separately identify extension services that are actively requested by farmers from unsolicited extension services of which the household is merely a passive recipient.

Given that the agricultural and non-agricultural domains are likely not separable in the context we study (see Benjamin, 1992; LaFave and Thomas, 2016), one should be worried that there may be other channels than the one implied by our model that account for the observed link between non-agricultural shocks and demand for extension. Our data allow us to assess the empirical plausibility of several other potential channels in this context, but we do not find strong evidence in favor of those alternative explanations. In particular, there is evidence that suggests that the effect of non-agricultural shocks is not due to an increased need for credit (e.g., driven by shocks to non-farm income and remittances) or because non-agricultural shocks (some of which may affect household labor supply) work through a demand for advice on labor inputs. Overall, our modeling insights are more broadly applicable and the empirical support for the model provided in this paper suggests that scarce attention may be part of explanations for phenomena in economic development, including beyond the specific application studied here.

The remainder of the paper is organized as follows. Section 2 discusses related literature and provides further background on agricultural extension services. Section 3 presents the model and derives predictions about farmers' demand for agricultural advice. Section 4 provides empirical evidence on the predictions of the model and addresses alternative explanations. Section 5 concludes.

2 Related literature and background on extension services

2.1 Related literature

Our paper contributes to several different literatures. First, we add to the recent literature in development economics that tries to explain low levels of technology adoption and low

[5] The empirical work is based on survey data from the Living Standard Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) database (World Bank, 2018).

input use in agriculture, in particular in Sub-Saharan Africa. Various channels have been considered in this literature, including market imperfections related to finance and insurance (Moser and Barrett, 2006; Dercon and Christiaensen, 2011; Karlan et al., 2014), uncertainty about quality and returns (Suri, 2011; Bold et al., 2017), individual and social learning (Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Conley and Udry, 2010; Hanna et al., 2014), high cost of providing information if schooling levels are low (Schultz, 1964), limited attention and other informational frictions (Cole and Fernando, 2013; Casaburi et al., 2014; Van Campenhout et al., 2017; Naeher, 2020), as well as behavioral biases (Duflo et al., 2011). Indeed, some of these channels have been shown to be important across a variety of contexts. While some of the related papers have highlighted the role of scarce mental resources in determining farm outcomes, this paper suggests a new specific channel based on (imperfect) demand for advice through which limited attention affects agricultural input choices and productivity, and provides empirical support for this channel.

Second, we contribute to the literature on the determinants and constraints of the use of agricultural extension services and their returns. The theoretical power to transform agriculture in developing countries has prominently been described by Schultz (1964). An important question in this literature is why extension services are not demanded more widely by farmers despite a growing body of evidence that extension services can have positive effects (see the studies cited in Section 2.2). One possible explanation is that the findings in these studies that show fairly large returns to extension cannot be generalized beyond the specific settings they study. Further, benefits may be heterogeneous, and extension may benefit only a small share of farmers. For example, the content (see Duflo et al., 2008) or the timing (Cole and Fernando, 2013) of advice provided may not be adequate for all households, especially in contexts where there is large information loss along the advice chain so that extension field staff do not fully understand themselves the advice they are to provide (Niu and Ragasa, 2018). We do not rule out the possibility that low (expected) returns to extension are part of the explanation of low demand. Instead, we introduce a novel mechanism to this discussion which we argue may be part of the explanation for the low demand for extension.

Third, we add to the body of literature that studies the role of attentional constraints for economic decision making. Such constraints can take different forms. For example, attention has been modeled as a stimulus-driven allocation process, emphasizing the importance of salient aspects of different pieces of information over the true informational value they carry (Bordalo et al., 2013; Kőszegi and Szeidl, 2013).[6] In this paper, we follow the literature on rational inattention started by Sims (2003), which assumes that people

[6]In these models, attention allocation is exogenous to the decision maker and determined by external signals rather than by optimizing behavior. However, such models appear to be unsuited for explaining the positive correlation between farm-unrelated shocks and demand for agricultural advice that we find in the data. It seems reasonable to assume that non-agricultural shocks increase the salience of the affected

allocate their attention optimally across different pieces of information, incorporating the costs associated with acquiring and processing information (for recent surveys of the rational inattention literature, see Handel and Schwartzstein, 2018; Mackowiak et al., 2018). It should be noted, however, that the central predictions of our model (i.e., those that we test empirically) arise independently of the assumed structure of information processing and could therefore also be generated by a simpler model with costly mental effort or time needed to obtain and process information, not based on entropy reduction.[7] Nevertheless, using a rational inattention approach to model farmers' demand for advice offers several advantages. First, in the rational inattention literature agents are allowed to choose not only the precision of the signals (i.e., the allocated amount of attention), but also the distribution from which signals are drawn. The structure of information is therefore endogenously determined in these models rather than exogenously imposed, which reduces the number of required assumptions. Second, the rational inattention literature makes use of concepts from the field of information theory (most importantly entropy) which are well-understood and for which a wide range of mathematical tools are readily available. Finally, there is a growing body of empirical evidence providing support for the rational inattention approach (Gabaix et al., 2006; Caplin and Dean, 2013; Goecke et al., 2013; Bartoš et al., 2016; Ambuehl et al., 2018).[8]

Until now, applications of rational inattention have focused primarily on rich countries. By using the same approach to model farmers' demand for agricultural advice and extension services, this paper extends the analysis based on rational inattention to the development context.[9] The literature provides several reasons why constraints on information processing may be particularly relevant in the context of less-developed economies. First, people in the developing world (and poor farmers in particular) tend to have less access to information in pre-processed forms than people in richer countries, e.g., because of limited access to media and tools such as online search engines. Second, the poor are often unable to benefit from distraction-saving goods and services, such as stable electric-

(non-agricultural) domain, which in these models would reduce rather than increase farmers' attention to agriculture, including obtaining agricultural advice.

[7]Note that what is termed "attention" in the literature (and in our model) usually comprises both cognitive effort and time use more generally, since both are needed for processing information. As pointed out by Banerjee and Mullainathan (2008), the relevant aspect of time use in this context should be thought of as the "quality of time (i.e., mental focus)" rather than the "quantity of time" (p. 493).

[8]For a more detailed overview of different approaches to attention used in economics, including a comprehensive discussion of the assumptions underlying the rational inattention approach, see Handel and Schwartzstein (2018).

[9]Applications of rational inattention initially focused on macroeconomic contexts such as monetary transmission (Mankiw and Reis, 2002; Maćkowiak and Wiederholt, 2009), consumption dynamics (Luo, 2008; Tutino, 2013), and business cycles (Maćkowiak and Wiederholt, 2015). Further studies apply rational inattention in the areas of finance (Van Nieuwerburgh and Veldkamp, 2010; Kacperczyk et al., 2016), industrial organization (Sallee, 2014; Martin, 2017), and labor (Bartoš et al., 2016; Acharya and Wee, 2020). In the development context, some existing studies investigate the role of other (i.e., not entropy-based) forms of attention (Banerjee and Mullainathan, 2008; Beaman et al., 2014; Hanna et al., 2014).

ity and water supply, and thus have to dedicate more time and mental effort to everyday life problems (Banerjee and Mullainathan, 2008; Bick et al., 2018). Finally, an increasing body of evidence suggests that there exists a direct adverse effect of poverty on cognitive functioning, because poverty-related concerns can induce stress and thereby deteriorate available mental resources (Mani et al., 2013; Haushofer and Fehr, 2014). All of these factors tend to increase the mental costs for the poor to make well-informed choices and thus exacerbate the severity of limitations in cognitive capacity which all humans face.

Finally, the paper relates to the literature that studies ex-post strategies to deal with shocks, e.g., through increasing labor supply (e.g., Kochar, 1995; Jayachandran, 2006), taking children out of school (Jensen, 2000), or relying on informal insurance networks (Udry, 1995; Dercon, 2002). We show that seeking advice or participating in available training opportunities is one possible way to (at least partially) compensate for incurred welfare losses due to adverse shocks.

2.2 Background on extension services

Agricultural extension is commonly seen as a key component in increasing productivity and triggering sustainable economic growth in developing regions around the world. Many policy-related studies particularly emphasize the role that advisory services can play in reaching marginalized farmers, reducing food insecurity, and breaking patterns of persistent rural poverty (Chipeta, 2006; World Bank, 2008). In addition, agricultural extension is often perceived as an important instrument to address new challenges related to environmental degradation and climate change (IFAD, 2013; FAO, 2014).

The economic literature finds mixed evidence of returns of extension services.[10] It is, in general, not clear whether this is due to variation in the studied programs or to methodological challenges associated with evaluating programs in the absence of exogenous variation (Birkhaeuser et al., 1991; Anderson and Feder, 2007). Traditionally, most often advice provided to farmers takes the form of field visits by extension staff or other local delivery agents to farm households. Various studies find that these forms of advice can indeed have significant effects. For example, Dercon et al. (2009) find that receiving at least one extension visit reduces headcount poverty by 9.8 percentage points and increases consumption growth by 7.1 percentage points in rural Ethiopia. Bandiera et al. (2018) study a program in Uganda that involves local farmers as delivery agents. Farmers in treatment villages grow 17% more marketable crops, have 40% higher profits, and per capita consumption expenditure is 22% higher. Other modern approaches to provide advice employ information and communication technology (ICT), such as agricultural apps, consulting hotlines, and SMS-based reminders (Aker, 2011; Cole and Fernando, 2013;

[10]For example, in the survey by Birkhaeuser et al. (1991) 36 of 48 reviewed studies find positive and significant impacts of extension services.

Casaburi et al., 2014).[11] More efforts to increase farmers' access to agricultural advice are currently under way, e.g., the 'Netflix for Agriculture' initiative by Fabregas et al. (2017).

According to Anderson and Feder (2007), 80% of the world's extension services are publicly funded and delivered by civil servants. While in the past such programs have predominantly been characterized by top-down and supply-driven approaches, the focus has shifted in recent years toward making extension more demand driven (Anderson, 2007; Davis, 2008). Several factors have contributed to this development. First, the collapse of the Training and Visit (T&V) system[12] in the late 1990s has led to the rise of a more pluralistic model of providing and financing extension services, involving stronger decentralization, privatization, and involvement of NGOs and farmer-based organizations. This process has shifted the focus to the demand side of extension services by emphasizing the importance of increasing farmers' voice and participation as compared to traditional top-down approaches (Rivera and Alex, 2005; Birner and Anderson, 2007).[13] Second, the transformation in the agricultural extension sector towards demand-driven approaches has been linked to a more general paradigm shift in public sector reform toward responsive governance, which advocates accountability and empowerment to increase the effectiveness of public service provision (including in many other sectors such as health and education; see United Nations, 2005; Birner and Anderson, 2007). Finally, the rapid diffusion of information and communication technologies has contributed to the promotion of demand-driven approaches to extension, by reducing the cost and providing new possibilities for farmers to access agricultural advice based on their own individual-specific needs.

3 Theory: Demand for agricultural advice under costly attention

This section presents a stylized model that is able to explain (i) why farmers may rationally decide not to participate in extension services, and (ii) why non-agricultural shocks can increase farmers' demand for agricultural advice and participation in extension services. The model builds upon the following three main assumptions. First, farmers have access to sources of agricultural advice (e.g., extension services), and believe that engaging with these sources has a positive effect on production. Second, requesting and benefiting from

[11] Examples of such technologies include mobile phone apps and hotlines that offer farmers the possibility to acquire information about farm practices, weather, and relevant prices, as well as online systems where farmers can send photos or show crops affected by diseases to a web camera in order to receive advice on treatment. A survey of ICT-based agricultural extension programs is provided in Aker (2011).

[12] The T&V system was a public extension model promoted by the World Bank from 1975 until 1995 to increase the adoption of "Green Revolution" technologies (mainly high-yielding seed varieties, fertilizer, and other agrochemicals) in more than 70 countries (Anderson, 2007).

[13] In part, this may also have been driven by the need to achieve greater scope for cost recovery in order to facilitate privatization and contracting of extension services, which are core elements of the new pluralistic model (Anderson, 2007).

advice requires farmers to be attentive. Third, attention is a scarce resource and farmers have to allocate their attention between different areas of their life, including those not related to farming activities. Based on these features, we demonstrate how not only agricultural shocks (such as pests and irregular rainfalls), but also shocks which are not directly related to agriculture may be linked to farmers' demand for extension.[14]

3.1 Model

We study the decision problem of a farmer who faces choice problems in two distinct domains. The first domain captures decisions in the farmer's production process, e.g., related to crop types, usage of inputs, and other agricultural tasks. We refer to this as the agricultural domain (or simply A). The second domain captures all other decisions which require the farmer's attention, e.g., how to deal with the sickness or death of a household member. This is referred to as the non-agricultural (N) domain. For each domain, the farmer's choices are summarized in a single action, denoted by $a_i \in \mathbb{R}$, with $i \in \{A, N\}$. Let the optimal action in each domain be given by

$$a_i^* = \phi z_i, \tag{1}$$

where the random variable $z_i \sim \mathcal{N}(0, \sigma_{z_i}^2)$ describes the fundamental state of the economy which is initially unobserved by the farmer.[15] For example, one may think of z_A as capturing all relevant factors that determine the returns to different agricultural production choices, including current prices, demand for certain crops, and soil conditions. Let $\overline{u}_i^*$ denote the maximal payoff for domain i associated with the optimal action a_i^*. Choosing a suboptimal action, $a_i \neq a_i^*$, leads to a payoff that is smaller than $\overline{u}_i^*$. For example, in the agricultural domain, this may be the case if the farmer uses the wrong type of pesticide or a suboptimal quantity of fertilizer given the prevailing conditions (as captured by the realization of z_A).

In addition, we allow for exogenous events, denoted by ϑ_i, which directly reduce the payoff in each domain. For example, ϑ_A may capture harvest loss due to bad weather, and ϑ_N may capture theft of money. In contrast to z_i, these shocks cannot be compensated for by the farmer through selecting appropriate actions. Instead, any realization of ϑ_i unequal to zero induces a direct shift in the farmer's level of utility. The highest possible payoff in each domain is thus given by

$$u_i^* = \overline{u}_i^* + \vartheta_i, \tag{2}$$

[14]The model heavily draws on existing work in the rational inattention literature, particularly the framework presented by Maćkowiak and Wiederholt (2009) and Wiederholt (2010). Where possible, we follow the notation used by these authors.

[15]To keep the analysis tractable, we focus on the case where fundamentals are independent across domains, i.e., nothing can be learned about a fundamental by paying attention to the other fundamental.

which we write as $u_i^*(\vartheta)$ to simplify notation. The farmer seeks to select the optimal action in both domains, maximizing a concave utility function over the sum of payoffs received from a_A and a_N.

To make better decisions, the farmer can devote attention to available sources of information and thereby reduce uncertainty about the realized states z_i and associated optimal actions. For example, in the agricultural domain, this may correspond to the farmer contacting an extension officer, participating in a field school, or asking a neighboring farmer for advice. In modeling attention, we follow the literature on rational inattention started by Sims (2003) and quantify attention as reduction in Shannon entropy, a measure of the unpredictability of a random variable's realization.[16] Paying attention can be modeled as receiving a noisy signal

$$s_i = z_i + \epsilon_i \tag{3}$$

about the realization of z_i, where $\epsilon_i \sim \mathcal{N}(0, \sigma^2_{\epsilon_i})$.[17] In this case, the prior entropy of the random variable z_i and the posterior entropy that results from paying attention to the fundamental are defined as

$$H(z_i) = \frac{1}{2}\log_2(2\pi e \sigma^2_{z_i}) \quad \text{and} \quad H(z_i|s_i) = \frac{1}{2}\log_2(2\pi e \sigma^2_{z_i|s_i}). \tag{4}$$

Based on these two equations, the amount of attention, κ_i, devoted to the choice problem associated with each domain can be quantified as

$$\kappa_i = H(z_i) - H(z_i|s_i). \tag{5}$$

This equation states that the more attention is devoted to domain i, the better the quality of the acquired signal, and thus the larger the reduction in uncertainty (measured in entropy) about the realized state z_i.[18]

Capturing the idea that attention is a scarce resource, the farmer faces in each domain the cost $\mu_i \kappa_i$, where $\mu_i > 0$ denotes the unit cost of attention (e.g., opportunity cost of mental energy). Note that μ_i may differ across domains, because paying attention to one decision may be more demanding than paying attention to another decision, e.g., due to experience or education.

[16] It has been pointed out in the literature that the concept of rational inattention relies on relatively strong assumptions about people's ability to focus their attention on those pieces of information that are most worth attending to (Handel and Schwartzstein, 2018; Kremer et al., 2019). On the other hand, a growing body of empirical evidence supports the rational inattention approach (Gabaix et al., 2006; Caplin and Dean, 2013; Goecke et al., 2013; Bartoš et al., 2016; Ambuehl et al., 2018).

[17] As shown by Sims (2003), this represents the signal structure that an agent who can freely set the distribution of the signal would choose in the case of a quadratic objective function and normal priors. Normality of the signals is therefore an outcome of the model itself rather than an additional assumption.

[18] Notice that this differs from standard models in economics based on rational expectations, which assume that agents are able to be perfectly attentive to all available information (i.e., agents can process information instantaneously and without any additional cost).

Overall, the decision problem of the farmer consists of choosing how much attention to devote to each of the two domains, and which actions to perform conditional on the received signals. The timing of the model is such that the farmer first observes the realizations of the shocks ϑ_i, then chooses the allocation of attention, receives the signals, and finally selects the actions.

Formally, this can be described as a decision problem with two stages. In the second stage, the farmer chooses the actions with the highest expected payoff given the received signals:

$$\max_{a_A, a_N \in \mathbb{R}} \quad E\left[u\left(a_A, a_N, z_A, z_N, \vartheta\right) | s_A, s_N\right], \tag{6}$$

where $\vartheta = (\vartheta_A + \vartheta_N)$. Let $\hat{a}_i$ denote the optimal action for domain $i \in \{A, N\}$ chosen by the farmer, i.e.

$$\hat{a}_i = \arg\max_{a_i \in \mathbb{R}} E\left[u\left(a_i, z_i, \vartheta\right) | s_i\right]. \tag{7}$$

In the first stage, the farmer observes the realization of the shocks ϑ_i and chooses the allocation of attention. In doing so, the farmer maximizes the expected utility resulting from the action chosen in the second stage less the cost of attention. Formally, in the first stage, the farmer solves

$$\max_{\kappa_i \geq 0} \quad E\left[u\left(\hat{a}_i, z_i, \vartheta\right)\right] - \sum \mu_i \kappa_i, \tag{8}$$

subject to the constraint on information processing (5) and equation (7). The farmer anticipates the actions chosen in the second stage and the associated expected payoffs when deciding how much attention to devote to each domain.

3.2 Solution and predictions

In deriving the farmer's optimal behavior, we focus on the case of a strictly concave utility function under quadratic approximation. This is a common approach in the literature on rational inattention (e.g., Maćkowiak and Wiederholt, 2009; Gabaix, 2014). The solution to the farmer's optimization problem is formally derived in Appendix A. Based on the resulting optimal allocation of attention, the model gives rise to a number of predictions which are summarized in the following two propositions.

Proposition 1. *A rationally inattentive farmer will pay more attention to the agricultural domain and thus be more likely to request advice, (i) the more costly are mistakes in a_A, (ii) the larger the prior uncertainty about the optimal action a_A^*, and (iii) the smaller the cost of paying attention to the fundamental z_A.*

Proof. See Appendix A. □

According to the results in Proposition 1, factors which make it easier for farmers to pay attention to agricultural advice, or which cause suboptimal cultivation practices

to be relatively more costly, will make it more likely that farmers request advice. This suggests that we should expect household characteristics which affect the costliness of paying attention to advice to be correlated with farmers' demand for extension services. For example, characteristics such as high age and low education are often argued to be positively related to individuals' attentional costs (Greenwood and Parasuraman, 1991; Ambuehl et al., 2018). In addition, one might expect demand for agricultural advice to be positively correlated with household size, given that households with fewer members feature less resources (such as time and cognitive capacity) and are thus more constrained in their capacity to participate in extension programs (other factors equal).

Notice that the results in Proposition 1 are exclusively based on parameters associated with the agricultural domain itself. In addition, the overarching utility function in the farmer's objective, which connects both domains through the channel of imperfect attention, gives rise to cross-domain effects, i.e., effects on farmers' demand for agricultural advice arising from parameters of the non-agricultural domain. This feature of the model is summarized in Proposition 2.

Proposition 2. *If attention is costly (i.e., $\mu_i > 0$), negative shocks in any of the two domains will cause the farmer to increase the amount of attention allocated to a_A, and thus raise the probability that agricultural advice is requested.*

Proof. See Appendix A. □

The mechanism behind the results in Proposition 2 is as follows. In equilibrium, the farmer allocates the amount of attention to each domain for which the marginal cost of attention (captured by the parameter μ_i) equals the marginal return (i.e., the increase in expected utility that results from a better signal due to more attention). A negative shock to the farmer's income or wealth lowers the absolute level of utility, which, under a concave utility function, leads to a larger marginal utility of income from farm activity. Therefore, the farmer is more willing to devote costly attention to advice that can help to raise productivity. Hence, the model predicts that farmers who are negatively affected by shocks will be more willing to devote attention to sources of agricultural advice, and thus be more likely to actively demand extension services. Importantly, this holds for both agricultural shocks and shocks that are not directly related to farming.[19]

Discussion. In the case of agricultural shocks, the predicted effect in Proposition 2 seems relatively unsurprising, and could in principle also be generated by other existing models. This applies less to shocks which are not directly related to agriculture. In the large body

[19]Notice that, because the model is symmetric in the two domains, a negative shock to income in any domain will also increase the amount of attention paid to a_N. Since we are mainly interested in studying the determinants of farmers' demand for agricultural extension, the empirical part below focuses on the cross-domain effect described in Proposition 2. Note also, that the model makes no assumption on whether the shocks ϑ_i are correlated across the two domains.

of literature that uses learning models to explain agricultural production decisions (e.g., Foster and Rosenzweig, 1995; Munshi, 2004; Conley and Udry, 2010), farmers are typically perceived as facing an initial lack of knowledge about optimal input targets, which can be progressively overcome through learning (based either on own experimentation or learning from others). In such an environment, agricultural shocks that affect optimal input targets (e.g., pest outbreak or change in the prices of agricultural inputs) will create a renewed need for farmers to learn, and thus tend to increase the demand for advice. However, these models would predict no such effect for shocks that are unrelated to farming, i.e., shocks that do not affect optimal cultivation practices.

Other studies in this context stress the importance of constraints resulting from prevailing market imperfections in developing countries, but perceive farmers as rational decision makers under full information (Schultz, 1964; Bardhan and Udry, 1999). An important insight of these studies is that farmers' optimal production choices may not be perfectly separable from consumption choices (as would be the case in the absence of market imperfections). This non-separability implies that optimal decisions in the agricultural domain may also be affected by shocks originating in the non-agricultural domain. For example, this would be the case if shocks to households' off-farm income also lead to changes in the optimal level of modern agricultural input use (which would not happen if farmers had access to perfect credit markets), or if optimal farm decisions are sensitive to shocks that affect the availability of family labor (which would not be the case if farmers could hire from perfect labor markets).

However, it is important to note that, due to their strong assumptions on rational decision making, these models face difficulties in explaining demand for advisory services in general. In particular, it remains unclear from these models why, in the absence of any information frictions, there would be a need for agricultural advice in the first place. Furthermore, assuming that there was a need, these models are unsuited to explain why farmers in Sub-Saharan Africa are not more widely making use of available extension services, especially in situations where those services are available free of charge.

Finally, it should be noted that the prediction in Proposition 2 runs counter to much of the recent literature on psychology and poverty (e.g., Banerjee and Mullainathan, 2008; Mani et al., 2013; Haushofer and Fehr, 2014), according to which negative shocks in the non-agricultural domain would tend to absorb cognitive bandwidth, leading to less attention paid to agricultural production and thus less use of agricultural advice. When testing the predictions of the model empirically, these effects clearly work against us. To the extent that we still find evidence in line with Proposition 2, the fact that our model based on rational inattention does not capture these cross-domain effects in terms of available cognitive bandwidth is therefore less of a concern.[20]

[20]The same argument applies to the concern that farmers' demand for advice could also be explained based on a similar model using time rather than attention as the limiting factor, where for some types

In sum, standard modeling approaches, e.g. based on learning or credit constraints, have difficulties explaining the combination of low levels of demand for extension and a (positive) reaction of demand for extension to non-agricultural shocks. On the other hand, our model with costly attention would be consistent with non-agricultural shocks explaining changes in demand for extension and we verify this prediction of the model below. Because it is conceivable that non-agricultural shocks are linked to demand for extension through other channels (e.g., due to non-separability), the empirical part below also discusses the evidence in light of some alternative theories.

4 Empirical evidence

In this section, we first show that there is statistically strong and robust evidence that, in line with the model, non-agricultural shocks are indeed associated with increased demand for extension. In addition, we assess the plausibility of some alternative explanations which might also account for the observed link. Our model is based on the assumption that agricultural advice has positive effects on farmers' production. To complement the existing evidence, cited in the introduction, we therefore also investigate the relationship between agricultural advice, farm decisions, and outcomes in our data (see Appendix D). While our data allow us to improve upon prior literature that also uses observational data to study the effects of extension services, we stress that the observational nature of the data limits our ability to make causal claims.

4.1 Data and descriptive statistics

The empirical work is based on survey data from three countries in Sub-Saharan Africa (Malawi, Nigeria, and Uganda), which were collected as part of the World Bank's Living Standard Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA).[21] In each country, households are selected in a nationally representative way and tracked over time, such that we can use a panel dataset consisting of three rounds of surveys in Malawi (2010-11, 2013-14, 2016-17) and Nigeria (2010-11, 2012-13, 2015-16), and four rounds in Uganda (2009-10, 2010-11, 2011-12, 2013-14).[22] We focus on households that engage in agricultural activities and report having cultivated at least one plot in a given season (for countries with two cropping seasons, i.e., Malawi and Uganda, we focus our analysis on the

of non-agricultural shocks (e.g., illness of a family member) the opportunity cost of time would increase and thus demand for agricultural advice would tend to decline.

[21] The same data are used by Deininger et al. (2017), Gollin and Udry (2017), and Sheahan and Barrett (2017).

[22] Detailed information about the design and implementation of the surveys in each country can be found at World Bank (2018). While the LSMS-ISA database covers more countries, only the data from the three countries we use here allow for separately identifying extension contacts that were actively solicited by farmers from extension services for which households were merely passive recipients. As we are interested in studying farmers' own demand for extension, we focus on these three countries.

main season). Starting with 36,014 household-wave observations in the original dataset, dropping 9,359 observations that report not having engaged in agricultural activities, and then dropping 1,381 observations without cultivated plots, leaves us with a maximum of 25,274 household-wave observations, comprising 11,154 households and 50,478 plot-wave observations. In all of the main regression analyses we work with household fixed effects, which requires two rounds of data. After dropping 748 observations with missing data on the use of agricultural advice, 162 observations with missing data on shocks, and 755 observations with missing data on one of the key household level control variables, the subsample of households that appear in the data for at least two rounds consists of 20,233 household-wave observations.

The rest of this section describes the construction of the key variables used to test the model's predictions. Additional information on the construction of variables and differences in survey designs across countries can be found in Appendix B, together with a complete list of all variables and basic summary statistics (see Table A1).

Extension services. In all three countries, the LSMS-ISA surveys collect detailed information on whether households received advice related to farming activities, as well as the number of extension contacts and the sources of advice (e.g., governmental extension service, NGOs, or other farmers). The dummy variable *Advice* indicates whether a household has received advice related to farming at least once over the past 12 months. The dummy variable *Extension* considers only advice that was obtained through sources other than media (i.e., sources such as TV, radio, or flyers). The variable *Contacts* contains the number of extension contacts, which includes visits to the household as well as visits by the household to the source.[23]

In addition, the data allow us to separately identify extension contacts that were actively solicited by farmers from extension services for which the household was merely a passive recipient. The former is captured by the variable *Solicited Contacts*, which is the sum of visits to the household solicited by the farmer, and visits by the household to the source. The dummy variable *Solicited Extension* equals one if the household had at least one such actively demanded contact in the past 12 months.

Table 1 provides a first impression of farmers' exposure to extension services in the studied countries. In this table we focus on the variable *Extension*, i.e., on dimensions of advice that exclude advice obtained through media. On average, 29% of farmers report having received such advice. In Malawi (which generates 32% of its GDP in the agricultural sector and is known for its relatively strong policy focus on agriculture, see

[23]It should be noted that while, in all three countries, the survey questions underlying our extension variables refer exclusively to received advice and information, we cannot exclude the possibility that some farmers maintain contacts with extension services also in order to receive other forms of support (e.g., financial or in-kind support). Note also, that extension services will likely be heterogeneous even within countries.

Table 1: Exposure to agricultural advice in last 12 months

Description	Full Sample	Malawi	Nigeria	Uganda
Households who received agricultural advice (% all HH-year obs.)	28.7	46.5	16.7	26.0
of those:				
Average number of contacts	4.5	4.1	5.4	4.1
More than 2 contacts (%)	51.6	52.8	60.9	41.1
More than 10 contacts (%)	9.1	5.6	12.5	9.1
Received advice rated as useful or very useful[a] (%)	84.6	80.0	91.2	87.0
Received advice rated as useless or bad[a] (%)	8.0	8.8	3.3	9.9
Paid in order to receive advice (%)	7.6	0.9	14.2	13.5
Households who solicited advice (% all HH-year obs.)	19.5	35.0	12.4	15.3
Households who solicited advice (% HH-year obs. with advice)	76.0	89.3	76.5	60.1
Share of solicited contacts (% all contacts)	73.6	80.8	64.2	75.8
Observations	24,526	7,222	8,844	8,460

Notes: Agricultural advice measures in-person advice and excludes advice received through media (TV, radio, flyers, etc.). [a]Exact wording differs between countries (see Appendix B). *Source:* Authors' calculation based on survey data from the LSMS-ISA database (World Bank, 2018).

OECD/FAO, 2016), the number is 46%. Conditional on receiving advice, farmers have an average of 4 to 5 contacts a year. While 52% of farmers receiving advice report more than two contacts a year, only a few farmers seem to be involved in regular extension programs (such as monthly village or field school meetings). The majority of farmers (85%) that receive advice rate the received advice as useful, and less than 10% of farmers report having received advice that was useless. On average, less than 8% of households that received advice paid anything for it.[24] In addition, Table 1 indicates that in all countries the majority of extension contacts are solicited by farmers. The share of solicited contacts ranges between 64% in Nigeria to over 80% in Malawi (possibly reflecting the fact that Malawi features a relatively decentralized and demand-driven extension landscape; see Davis, 2008). More details are provided in Table A2 in the appendix.

Table 2 provides additional insights into the topics on which farmers receive advice. Almost all farmers (91%) who have been in contact with extension services received advice on agricultural production and processing. To a large extent, this involves advice about modern agricultural inputs such as new seed varieties, fertilizer, and pesticides. In addition, a third of farmers report having received advice on livestock production and animal care. With respect to different sources of agricultural advice, Table A3 in the appendix shows that government extension services are responsible for 79 to 94% of extension provided in Uganda and between 32 and 49% in Malawi. In Nigeria, where public extension programs seem to be less prevalent, farmers report receiving advice relatively more often from private extension services and from other farmers.

[24]Conditional on paying for advice, the average amounts paid are USD 6 in Uganda, USD 9 in Nigeria, and USD 18 in Malawi.

Table 2: Topics of advice

Description[a]	Full Sample	Malawi	Nigeria	Uganda
Agricultural production and processing	91.3	92.6	80.1	96.3
New seed varieties	50.7	51.3	49.2	
Fertilizer	52.6	50.0	58.9	
Pest control	29.0	28.3	30.8	
Composting/manure	41.8	50.3	21.0	
Irrigation	26.5	34.5	6.9	
Marketing and crop sales	25.9	17.2	24.6	39.9
Livestock production	32.8	20.2	26.7	55.8
Animal diseases and vaccination	30.5	18.8	28.1	50.0
Fishery	8.1	7.9	1.9	12.4
Forestry	15.7	21.3	2.3	
Access to credit	12.8	15.8	5.5	
Other	2.1	2.8	0.5	
Observations (HHs who received advice)	6,877	3,336	1,369	2,172

Notes: Numbers are percentages of households who received advice on indicated topic, conditional on having received in-person advice (i.e., excluding advice received through media). [a]Exact wording differs between countries. *Source:* Authors' calculation based on survey data from the LSMS-ISA database (World Bank, 2018).

Shocks. Data on shocks are available at the household level and include detailed information on whether households have been negatively affected by any shocks over the past year and the type of each shock.[25] The latter is collected based on a list of around 20 different events, which are very similar across countries. To test the predictions of the model, we classify shocks as either directly related to agriculture (*AgShock*) or not directly related to agriculture (*NonAgShock*). Table 3 provides a complete list of the shock items that appear in the data and the assigned categories for our baseline regressions.[26] As can be seen in the table, agricultural shocks include events such as "irregular rains", "unusual high level of crop pests", and "livestock disease". Non-agricultural shocks include events such as "illness of a household member", "theft of money", and "end of regular assistance/remittances".[27] Of course, any classification of the shock items listed in Table 3 into two distinct groups related to agriculture and not directly related to agriculture will be imperfect. We therefore explore several alternative classifications as part of the robustness tests.

[25]As described above, there are several years between panel rounds, and these are inconsistently spaced over time and countries. Therefore, we do not work with lagged shocks, as these are (i) several years, and therefore, in our view, too far in the past, and (ii) irregularly spaced.

[26]The shock items "other" and "increase in the prices for food" are not classified in our baseline regressions since we found it difficult to attribute them to either of the two shock variables. As shown below, our results are robust to including "increase in the prices for food" in *AgShock* or in *NonAgShock*.

[27]As can be seen in Table 3, the extent to which households report experiencing negative shocks differs considerably between countries. For example, in Nigeria only 12% of farmers report having been negatively affected by agricultural shocks (on average during one year), while in Malawi and Uganda the corresponding percentages are 82% and 41%, respectively.

Table 3: Shocks to households by country

Description[a]	Percentage of household-wave obs. with shock (on average during one year)				Percentage of households with transition in shock (across survey rounds)			
	Malawi	Nigeria	Uganda	Full Sample[b]	Malawi	Nigeria	Uganda	Full Sample[b]
Agricultural shock (AgShock)	82.1	12.0	40.6	43.3	20.5	24.3	43.2	28.9
Drought/irregular rains	60.6	2.8	35.9	31.9	34.4	6.2	42.3	28.3
Floods/landslides	11.4	5.5	4.8	7.0	11.3	11.5	8.5	10.5
Crop pests or disease	14.4	0.8	3.2	5.8	15.9	2.0	6.4	8.7
Livestock disease	14.8	1.8	1.7	5.7	16.3	4.5	3.7	8.7
Increase in price of agricultural inputs	60.3	2.2	1.7	19.6	36.2	5.4	3.3	16.4
Fall in price of agricultural output	26.8	0.7	1.6	8.9	27.1	1.7	3.4	11.8
Non-agricultural shock (NonAgShock)	40.1	14.1	15.7	22.5	32.5	27.3	26.0	28.9
Health								
Illness or accident of household member	16.1	2.6	8.1	8.6	17.0	6.1	15.8	13.3
Death or disability of household member	9.4	3.7	3.1	5.2	9.9	8.5	5.8	8.2
Income								
Loss of employment	4.5	0.2	0.1	1.5	3.1	0.4	0.2	1.4
Reduction in non-farm income	10.0	2.2	0.3	3.9	9.0	4.8	0.8	5.1
End of assistance/remittances	8.9	1.9		5.2	9.1	4.6		7.0
Crime								
Theft of money/valuables	10.5	2.2	4.1	5.4	10.2	5.1	8.0	8.0
Conflict/violence	7.6	0.5	1.1	2.9	7.1	1.1	2.6	3.8
Other								
Fire/earthquake/other damage	6.6	2.4	0.8	3.1	6.6	5.8	1.6	4.8
Not classified								
Increase in prices for food	59.7	8.2		32.2	39.3	18.0		29.8
Other (not specified)	11.4	1.2	2.5	4.7	11.6	2.8	5.2	6.9
Observations	7,517	8,578	8,686	24,781	4,151	3,340	3,487	10,978

Notes: [a]Exact wording differs between countries. [b]The full sample is obtained by pooling data across countries and waves. *Source:* Authors' calculation based on survey data from the LSMS-ISA database (World Bank, 2018).

Household characteristics. We control for unobserved factors that are fixed at the household level via the inclusion of household fixed effects. In addition, we control for time-varying characteristics, including household size and composition as well as educational level, age, and gender of the household head.

4.2 Testing the model's predictions

The regression model we estimate is given by

$$Extension_{it} = \alpha_0 + \alpha_1 AgShock_{it} + \alpha_2 NonAgShock_{it} + \alpha_3 X_{it} + \mu_i + \omega_t + \epsilon_{it}, \quad (9)$$

where the dependent variable is a measure of farmers' exposure to extension services (in some specifications, we restrict the dependent variable to services that were actively requested by farmers). $AgShock_{it}$ is a dummy variable that captures shocks which affect optimal cultivation practices and are therefore directly related to farmers' need for advice (e.g., to inquire about optimal pest control after a pest outbreak). $NonAgShock_{it}$ is a dummy that corresponds to shocks which have a negative effect on farmers' income or wealth, but do not constitute an immediate reason to request advice about farming activities (e.g., theft of money or non-farm business failure). The terms μ_i and ω_t denote household and wave fixed effects. Finally, X_{it} is a vector of time-varying household-level variables.

The hypothesis we test is that both coefficients α_1 and α_2 in equation (9) are positive (see Proposition 2). In addition, the model predicts that characteristics that make it easier for farmers to pay attention to agricultural advice, or factors that cause suboptimal cultivation practices to be relatively more costly, will make it more likely that farmers request advice (Proposition 1). Therefore, we expect household characteristics such as education and household size to be correlated with farmers' demand for extension (with the directions discussed in Section 3.2).

Our empirical strategy relies on the comparability of households that receive non-agricultural shocks and those that do not receive shocks. Table A4 in the appendix shows mean characteristics of households that report different types of shocks and characteristics of households without shocks. The comparison suggests reasonably comparable groups. In addition, our regressions capture fixed differences between households through the included household fixed effects.

Table 4 reports estimates of the regression model specified in equation (9) for various measures of farmers' exposure to agricultural advice. In the first three columns, the dependent variable is an indicator that equals one if in a given season the household received any advice related to farming (i.e., from any of the sources listed in Table A3). The dependent variable in columns (4) to (6) excludes advice that is obtained through media (TV, radio, flyers, etc.). In columns (7) to (9), the indicator for extension is

Table 4: Test of model predictions

	(1) Advice	(2) Advice	(3) Advice	(4) Extension	(5) Extension	(6) Extension	(7) Solicited Extension	(8) Solicited Extension	(9) Solicited Extension
AgShock	0.094***	0.089***	0.087***	0.079***	0.074***	0.072***	0.065***	0.062***	0.061***
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
NonAgShock	0.033**	0.033**	0.033**	0.031**	0.032**	0.030**	0.025***	0.026***	0.025***
	(0.030)	(0.024)	(0.022)	(0.030)	(0.025)	(0.029)	(0.008)	(0.007)	(0.007)
Adults		0.020***			0.022***			0.020***	
		(0.002)			(0.001)			(0.000)	
Children		0.013***			0.010***			0.010***	
		(0.000)			(0.003)			(0.001)	
Primary educ. (head)		0.012			0.015			0.003	
		(0.576)			(0.374)			(0.895)	
Secondary educ. (head)		-0.008			-0.003			0.001	
		(0.767)			(0.897)			(0.980)	
Age head		0.012**			0.009			0.008*	
		(0.015)			(0.106)			(0.078)	
Age head sq.		-0.000**			-0.000			-0.000*	
		(0.015)			(0.130)			(0.070)	
Male head		0.027			0.012			0.013	
		(0.363)			(0.666)			(0.492)	
HH FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Full set of control dummies			yes			yes			yes
Observations	20,392	20,392	20,392	20,392	20,392	20,392	19,653	19,653	19,653
R-squared (within)	0.024	0.030	0.039	0.020	0.024	0.033	0.011	0.017	0.026
R-squared (total)	0.074	0.031	0.031	0.049	0.025	0.026	0.037	0.024	0.027
Mean dep. var.	0.335	0.335	0.335	0.285	0.285	0.285	0.197	0.197	0.197

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). The omitted category for education is "no schooling". Full sets of control dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

further restricted to solicited advice, i.e., the dummy is only equal to one if the household actively requested advice. The results in Table 4 show that, irrespective of whether a set of household controls is included or not, both agricultural shocks and non-agricultural shocks are positively correlated with receiving agricultural advice (full sets of dummies are included as controls in columns 3, 6, and 9). In all specifications, the estimated coefficients of the two shock indicators are statistically highly significant. As discussed in more detail below, the results are robust to different ways of clustering standard errors and to alternative definitions of the considered shock and extension variables. We thus interpret the findings in Table 4 as being in line with the predictions of the model (as described in Proposition 2) and providing empirical support for the suggested limited attention channel.

Although the results in Table 4 are in line with the predictions of our model, we also note that they imply that the quantitative magnitude of the link between non-agricultural shocks and demand for advice is modest. More specifically, the estimated coefficients of *NonAgShock* in columns (7) to (9) suggest that one out of 40 (or 2.5%) of farmers actively seeks agricultural advice in response to a non-agricultural shock. While these estimates are consistent with attentional constraints being part of the low demand for extension, they also highlight that costly attention is only one of several pieces of the puzzle to explain the low demand for extension.

Furthermore, the results in columns (2), (5), and (8) of Table 4 show that farmers' decisions to request advice and participate in extension programs are positively correlated with household size. Of course, we cannot interpret this finding as causal, but the positive correlation is consistent with the model. From the perspective of the model, this finding could be attributed to the fact that additional household members represent additional resources (such as time and cognitive capacity), which are useful in obtaining and processing information. Thus, when households that are similar along other characteristics are compared, those with more members will find it relatively easier to request and implement agricultural advice. In contrast, households with fewer members may be more constrained in their capacity to participate in extension programs, which will tend to reduce the number of contacts and lead to a lower probability of requesting advice.[28] While there seems to be a positive relationship between age of the household head and access to extension services, we do not find significant results for gender and education

[28] A similar line of reasoning is used by Gido et al. (2015) to rationalize the finding of a negative link between off-farm income and extension contacts in Kenya. Regarding the positive coefficient of the number of children, notice that the mechanism would only apply to children old enough to participate in working on the farm, thus representing additional resources rather than a liability (which, among the rural households in our sample, might start at a fairly young age). However, for very young children there might be another explanation in line with our model. A newborn baby might have a similar effect as a negative shock to household income, i.e., marginal utility of additional income increases as part of the income is diverted to the baby.

Table 5: Test of model predictions: Disaggregated shocks

	(1) Solicited Extension	(2) Solicited Extension	(3) Solicited Extension	(4) Solicited Extension	(5) Solicited Extension
AgShock	0.061***	0.063***	0.061***	0.062***	0.060***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
NonAgShock	0.025***				
	(0.007)				
NonAgShock (Health only)		0.022**			0.017*
		(0.030)			(0.066)
NonAgShock (Income only)			0.055***		0.049**
			(0.008)		(0.013)
NonAgShock (Crime only)				0.046**	0.041**
				(0.020)	(0.041)
HH FE	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes
Observations	19,653	19,653	19,653	19,653	19,653
R-squared (within)	0.026	0.025	0.026	0.026	0.027

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). [a]The number of observations in column (5) is smaller, because the shock item "End of assistance/remittance" is not available in Uganda (see list of shock items in Table 3). Included shock items are as follows: Health ("Illness or accident of HH member", "Death or disability of HH member"), Income ("Loss of employment", "Reduction in non-farm income", "End of assistance/remittances"), Crime ("Theft of money/valuables", "Conflict/violence"). As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

of the household head, nor for the highest educational level of any household member.[29] The latter may not be surprising, given that we control for household fixed effects, which implies that there is little variation remaining in education variables.

Our model does not consider heterogeneity in the agricultural shocks. The model assumes that advice is valuable with any agricultural shock. Yet, empirically, the timing and the type of shocks likely matters. Shocks early in the season may be more amenable to action and consequently the value of advice may be higher than in the case of shocks later in the season. Similarly, some shocks may be such that even with advice there is not much the farmer can do (e.g. if the field is flooded for a large part of the season). Unfortunately, we do not observe the precise timing of shocks and seeking advice. We also cannot cleanly identify shocks for which the value of advice would be high. However, both of these issues will likely work against us, i.e., will make it less likely that we find a correlation. To the extent that we still find a correlation between shocks and seeking advice, the inability to distinguish the timing of shocks better is therefore less of a concern.

[29]Note that age of the household head does not simply pick up time trends when including household and wave fixed effects, but also varies over time when the household head changes (e.g., the head dies and the spouse or one of the children becomes the new head).

One may be worried about the role of individual components of the aggregate non-agricultural shock measure. Therefore, in Table 5 the dummy variable *NonAgShock* is split into individual types of shocks, focusing separately on shocks related to health, income, and crime. The first column in Table 5 repeats the estimation results from the main specification (column 9 in Table 4). In column (2), only shocks related to health are used to construct the non-agricultural shock dummy variable. Columns (3) and (4) repeat the same approach for shocks related to income and crime. In column (5), all three types of non-agricultural shocks are included simultaneously. Overall, the results in Table 5 indicate that the link between non-agricultural shocks and farmers' demand for extension is statistically robust, even for separate categories of non-agricultural shocks.

We also perform placebo regressions. Specifically, we repeat the central regressions in Table 4 with the dependent variable *Unsolicited Extension*, which equals one for households that received only advice which they did not actively seek themselves. The idea is that, according to our theoretical model, unsolicited advice should not be affected by non-agricultural shocks. The results of these placebo regressions are shown in Table A9 in Appendix C. According to these results, there is no statistically significant link between non-agricultural shocks and unsolicited extension services. These findings suggest that it is not an unobserved variable that drives the correlation between non-agricultural shocks and extension services generally. Instead, this supports the hypothesis that there is a causal link from experiencing a non-agricultural shock to actively looking for advice.

Additional robustness checks with respect to clustering of standard errors, alternative variable definitions, and exclusion of household fixed effects are reported in Appendix C. As shown in Table A5, the model predictions hold when standard errors are clustered along both stratum and wave dimensions ("2-way"), when clustered at the district level (there are 158 districts), as well as for the cluster wild bootstrap procedure described in Cameron et al. (2008) to take into account the small number of clusters when clustering at the "stratum" level. Table A6 tests the robustness of the model predictions to alternative variable definitions. In columns (1) and (4), the extension indicators exclude advice which was provided by other farmers, because this constitutes a somewhat different approach to extension. In columns (2) and (5), the non-agricultural shock variable also contains the shock item "increase in prices for food", which was previously not classified. In columns (3) and (6), the food price shock item is instead included in the agricultural shock variable. For all specifications, the shock variables remain significant. Table A7 shows that the model predictions also hold when no household fixed effects and no household-level controls are included (see columns 1-4; columns differ in their way of dealing with clustering), and when only the household-level controls are included but not the household fixed effects (columns 5-8). In particular, comparing the results in Table A7 with those in Table 4 shows that adding household fixed effects changes the point estimates of the two shock variables but does not change the significance levels much (note that while

Table A7 reports results only for the dependent variable *Advice*, the findings are similar when we repeat the same procedure for *Extension* and *Solicited Extension* as dependent variables).

4.3 Discussion of alternative interpretations

One concern in assessing the predictions of the model is that non-agricultural shocks may also affect farmers' demand for extension by creating a need for advice on how to best operate under reduced availability of resources for purchasing farm inputs. This concern is particularly relevant given that the agricultural and non-agricultural domains are likely not separable in the context we study (Benjamin, 1992; LaFave and Thomas, 2016). For example, it might be the case that adverse shocks to households' wealth or non-farm income lead to changes in the optimal level of modern agricultural input use (if farmers have imperfect access to credit), or that optimal farm decisions are sensitive to shocks that affect the availability of family labor (see Section 3.2). In addition, farmers might contact extension workers after a non-agricultural shock simply because they hope to receive monetary or in-kind support rather than agricultural advice.

While our data do not allow us to completely rule out the possibility that some farmers solicit extension services for other reasons than requesting advice (see also footnote 23), we are able to obtain some useful insights by studying the link between shocks and farmers' demand for extension using disaggregated advice topics. In Table A8 in Appendix C, the considered dependent variables capture specific topics for which farmers demand advice (i.e., the dependent variables are only equal to one if the household actively requested advice of a particular category). While agricultural shocks show significant coefficients for all topics except "fishery", the non-agricultural shock variable is only significant for 'agricultural production and processing' and 'animal diseases and vaccination'. In particular, this suggests that the link between shocks and farmers' demand for extension is not due to an increased need for advice related to credit (see the insignificant results in column 7).

One might also wonder whether the link between incurred shocks and demand for extension may be due to reverse causality, i.e., an effect of received advice on the occurrence (or at least the perception) of shocks. While in the case of agricultural shocks we believe this might be a reasonable concern, it seems unlikely that this would also apply to non-agricultural shocks (which constitute the main prediction of the model that we test).

Another concern might be that farmers do not request extension services if these are believed to have small (or maybe negative) effects on profits. In addition to the evidence cited in the introduction, we therefore also perform an econometric analysis of the association between extension services and farm-level outcomes based on our data. The panel structure of the LSMS-ISA data allows us to make some progress in addressing the

endogeneity problems facing existing related studies that are based on observational data (see the survey papers provided by Birkhaeuser et al., 1991; Evenson, 2001), in particular through our ability to include farm fixed effects and proxies for agricultural shocks. Yet, obvious endogeneity concerns remain, due to the possibility that time-varying shocks – other than those that we can control for – affect both demand for extension and outcomes, and the results should be interpreted as suggestive correlations in the data. Results are reported in Appendix D. We find that access to extension services is positively associated with a number of relevant farm outcomes. This particularly holds for agricultural advisory services that are provided at farmers' own request. The quantitative magnitudes of our estimates imply that receiving agricultural advice is associated with a 7% larger value of harvest and 8% higher profits (defined as value of harvest net of costs for seeds, fertilizer, and agrochemicals).[30] Thus, as long as farmers' beliefs are consistent with the outcomes observed in the data, there is no reason to assume that farmers abstain from requesting extension services because they believe that the provided advice is not useful (also recall that more than 80% of farmers that received advice rate it as useful or very useful in our sample; see Table 1).

In addition to the ability to distinguish between solicited and unsolicited advice, the data also allow an analysis of potential channels through which extension might affect farm outcomes. We find a significant link between extension services and use of modern farm inputs (mainly fertilizer and improved seeds), which are commonly argued to be important determinants of agricultural productivity (Evenson and Gollin, 2003; Morris et al., 2007; Duflo et al., 2011).

Another concern might be that the observed correlation between shocks and received extension services may be driven by supply-side effects rather than the proposed mechanism through increases in farmers' demand for advice. For example, this might be the case if access to extension services was affected by limited supply (e.g., because these services are often understaffed), and the supply of extension is partly in response to adverse shocks. While to some extent this could be captured through fixed effects in the analysis, our data do not allow us to fully rule out the possibility that (part of) the observed correlation between shocks and received extension services is due to such supply side effects.

Finally, non-agricultural shocks may affect farmers' demand for extension by creating a need for advice on optimal farm practices with respect to labor inputs. Yet, in our analysis of the relation between receiving advice and farmers' production choices, we do not find evidence of a significant link between the amount of labor farmers allocate to

[30] We stress again that due to the endogeneity concerns stated above, we cannot interpret the estimates as causal. Note further that irrespective of these quantitative estimates, the mere observation of a positive association between shocks and solicited advice might be interpreted as an indication of farmers' perception that returns to participating in extension programs are indeed positive (otherwise they would not ask for extension in light of negative shocks).

their plots (including both family and hired labor) and participation in extension services (see Table A12 in Appendix D). Thus, our data seem to provide no empirical support for this concern.

5 Conclusion

In this paper, we study demand for advice in an agricultural setting. We first lay out a novel channel to explain farmers' demand for agricultural extension services. Second, we provide empirical evidence that is consistent with implications of the model. The empirical work makes use of a large recently collected panel dataset of farmers from three countries in Sub-Saharan Africa.

The theoretical insights we provide on the determinants of farmers' demand for agricultural advice and extension services center around the idea that participation in extension programs is only worthwhile if farmers devote sufficient attention to demanding, listening to, and implementing received advice. Based on this feature, we model farmers as rational decision makers facing a limited capacity to process information, causing attention to be a scarce resource. Our model gives rise to several interesting predictions. First, farmers' decision to request extension services will depend on the amount of attention they are willing to devote to their agricultural production process, as opposed to other areas of life. Second, negative shocks to household income or wealth can result in larger demand for agricultural advice. Importantly, this holds even for shocks which do not directly affect optimal farming practices and thus do not constitute an immediate reason for farmers to request agricultural advice.

Overall, the model suggests a specific channel through which limited attention affects agricultural input choices and productivity, based on (imperfect) demand for advice. The derived insights complement the existing literature in this context and can contribute to explanations for low demand for extension service. Specifically, the implications of our model complement the insights of Banerjee and Mullainathan (2008), who argue that "people may not be able to fully attend to their jobs if they are also worrying about problems at home, and being distracted in this way reduces productivity" (p. 489). The model we propose explains how scarce attention translates into low productivity even if outside help is available at low monetary cost. On the other hand, the model implies a link between shocks and increased attention to agricultural production: Non-agricultural shocks can raise farmers' marginal utility of additional income, consequently increasing their willingness to devote costly attention to agricultural production, leading to a higher probability that extension services are demanded. Given that participation in such programs translates into better production outcomes and eventually higher incomes, this mechanism may also be seen as adding to the spectrum of ways by which the poor respond to adverse shocks and ex post cope with risk.

When we assess the predictions of the model empirically, we find statistically strong evidence for the predicted link between non-agricultural shocks and farmers' demand for extension. The results are robust to various alternative specifications and also hold when individual types of non-agricultural shocks, such as health, income, and crime-related shocks, are separately considered. Yet, the size of the estimates suggests that the link between non-agricultural shocks and demand for advice is of a modest quantitative magnitude. Thus, while the empirical results are consistent with attentional constraints being part of the low demand for agricultural advice, costly attention is apparently only one piece of the puzzle to explain the low demand for advice. The empirical work also provides some evidence that suggests that the effect of non-agricultural shocks is not due to an increased need for credit or because non-agricultural shocks, some of which may affect household labor supply, work through a demand for advice on labor inputs. Yet, our analysis is limited by the available data and we clearly cannot rule out all plausible alternative explanations. More empirical research to investigate scarce attention as a possible limiting factor for further development in agriculture is warranted.

Overall, the findings in this paper highlight the possibility that farmers' optimal demand for advice and the decision to participate in extension programs are affected by constraints to information processing due to costly attention. Just as findings by Drexler et al. (2014) in the context of financial literacy suggest that simpler rules may sometimes be more helpful, our results point to the importance of designing advisory services in ways that minimize the cognitive burden associated with requesting and absorbing advice. Our results can thus be seen as providing support for recent initiatives which aim at making agricultural information more easily accessible to farmers in developing countries, including by increasing the availability of mobile phone-based services (Cole and Fernando, 2013; Casaburi et al., 2014) and developing new tools for farmers to obtain personalized, real-time advice from an interactive online database (Fabregas et al., 2017). In addition, our findings suggest that the timing of offering extension services matters, as farmers may be more willing to devote attention to listening to and implementing advice when they are facing a more pressing need to increase agricultural production – even if this need was caused by events unrelated to farming.

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APPENDIX

A Proof of propositions

In deriving the farmer's optimal behavior, we make the following simplifying restrictions and assumptions. First, we focus on the case where the utility function $u(.)$ is strictly concave, such that negative shocks ϑ_i that decrease the overall level of utility lead to a larger marginal utility of additional payoff. Second, we assume that $u(.)$ is twice continuously differentiable and the second derivative with respect to the chosen action takes a larger absolute value at lower levels of payoff. Third, we derive the optimal behavior for a quadratic approximation of the utility function around the solution of the model when $z_i = 0$ for $i \in \{A, N\}$, i.e., around the point $(a_i, z_i, \vartheta) = \left(\hat{a}_i^{\vartheta}, 0, \overline{\vartheta}\right)$ with $\hat{a}_i^{\vartheta} = \arg\max_{a_i \in \mathbb{R}} u\left(a_i, 0, \overline{\vartheta}\right)$. Let this point be denoted as $\overline{\pi}$, and let $\tilde{u}(.)$ denote the second-order Taylor approximation of the function $u(.)$ around $\overline{\pi}$. The approximation is given by

$$\begin{aligned}\tilde{u}\left(a_i, z_i, \vartheta\right) = u(\overline{\pi}) &+ \frac{\partial u}{\partial a_i}(\overline{\pi})(a_i - \hat{a}_i^{\vartheta}) + \frac{\partial^2 u}{\partial a_i^2}(\overline{\pi})\frac{(a_i - \hat{a}_i^{\vartheta})^2}{2} \\ &+ \frac{\partial^2 u}{\partial a_i \partial z_i}(\overline{\pi})(a_i - \hat{a}_i^{\vartheta})z_i + \frac{\partial^2 u}{\partial a_i \partial \vartheta}(\overline{\pi})(a_i - \hat{a}_i^{\vartheta})(\vartheta - \overline{\vartheta}) + r,\end{aligned} \tag{A.1}$$

where r contains terms that are independent of a_i. Using this approximation, the utility loss associated with choosing a suboptimal action $a_i \neq a_i^*$ is given by

$$\begin{aligned}\tilde{u}\left(a_i^*, z_i, \vartheta\right) - \tilde{u}\left(a_i, z_i, \vartheta\right) = &\frac{\partial u}{\partial a_i}(\overline{\pi})(a_i^* - a_i) \\ &+ \frac{1}{2} \cdot \frac{\partial^2 u}{\partial a_i^2}(\overline{\pi})\left[a_i^{*2} - a_i^2 + 2\hat{a}_i^{\vartheta}(a_i - a_i^*)\right] \\ &+ \left[\frac{\partial^2 u}{\partial a_i \partial z_i}(\overline{\pi})z_i + \frac{\partial^2 u}{\partial a_i \partial \vartheta}(\overline{\pi})(\vartheta - \overline{\vartheta})\right](a_i^* - a_i).\end{aligned} \tag{A.2}$$

As we are approximating around a local maximum, it holds that $\partial u / \partial a_i = 0$ and $\partial^2 u / \partial a_i^2 < 0$. Furthermore, taking the derivative of $\tilde{u}(.)$ in equation (A.1) with respect to a_i shows that the optimal action is determined by

$$\frac{\partial \tilde{u}}{\partial a_i} = \frac{\partial^2 u}{\partial a_i^2}(\overline{\pi})(a_i - \hat{a}_i^{\vartheta}) + \frac{\partial^2 u}{\partial a_i \partial z_i}(\overline{\pi})z_i + \frac{\partial^2 u}{\partial a_i \partial \vartheta}(\overline{\pi})(\vartheta - \overline{\vartheta}) \stackrel{!}{=} 0. \tag{A.3}$$

Denoting $\hat{u}_{11} = \partial^2 u / \partial a_i^2(\overline{\pi})$, $\hat{u}_{12} = \partial^2 u / \partial a_i \partial z_i(\overline{\pi})$, and $\hat{u}_{13} = \partial^2 u / \partial a_i \partial \vartheta(\overline{\pi})$, this implies that

$$a_i^* = \hat{a}_i^{\vartheta} - \frac{\hat{u}_{12}}{\hat{u}_{11}} z_i - \frac{\hat{u}_{13}}{\hat{u}_{11}}(\vartheta - \overline{\vartheta}). \tag{A.4}$$

Using these results, equation (A.2) can be simplified to

$$\begin{aligned}\tilde{u}\left(a_i^*, z_i, \vartheta\right) - \tilde{u}\left(a_i, z_i, \vartheta\right) &= \frac{\hat{u}_{11}}{2}\left[a_i^{*2} - a_i^2 + 2\hat{a}_i^{\vartheta}(a_i - a_i^*)\right] - \hat{u}_{11}(a_i^* - \hat{a}_i^{\vartheta})(a_i^* - a_i) \\ &= -\frac{\hat{u}_{11}}{2}(a_i - a_i^*)^2. \end{aligned} \tag{A.5}$$

Denoting the utility $\tilde{u}\left(a_i^*, z_i, \vartheta\right)$ obtained from the optimal action as $u_i^*(\vartheta)$, it thus follows that

$$\tilde{u}\left(a_i, z_i, \vartheta\right) = u_i^*(\vartheta) - \frac{\omega_i(\vartheta)}{2}(a_i - a_i^*)^2, \tag{A.6}$$

where $\omega_i(\vartheta) = |\partial^2 u/\partial a_i^2\left(\overline{\pi}\right)|$ depends negatively on ϑ due to the made assumptions about the properties of u. Working with the second-order approximation of the utility function in equation (A.6) greatly simplifies the further derivation, as it allows us to use the result from Maćkowiak and Wiederholt (2009) that the optimal action taken by a rationally inattentive agent who faces a quadratic objective function is simply given by the expected optimal action conditional on the received signal (i.e., there are no higher order effects involved, such as those related to risk aversion, when choosing actions). The decision problem of the farmer thus simplifies to

$$\max_{\kappa_A, \kappa_N \geq 0} \quad \sum_{i \in \{A,N\}} E_s\left[u_i^*(\vartheta) - \frac{\omega_i(\vartheta)}{2}(a_i - a_i^*)^2\right] - \sum_{i \in \{A,N\}} \mu_i \kappa_i \tag{A.7}$$

$$\text{s.t.} \quad a_i^* = \phi z_i \tag{A.8}$$

$$a_i = E[a_i^* | s_i] \tag{A.9}$$

$$s_i = z_i + \epsilon_i \tag{A.10}$$

$$\kappa_i = H(z_i) - H(z_i | s_i) \tag{A.11}$$

where condition (A.9) corresponds to the choice in the second stage of the original decision problem. The optimal allocation of attention can be derived as follows. First, combining equations (A.8) - (A.10) yields

$$E_s\left[\frac{\omega_i(\vartheta)}{2}(a_i - a_i^*)^2\right] = \frac{\omega_i(\vartheta)}{2}\phi^2 E\left[\left(E\left[z_i | s_i\right] - z_i\right)^2 | s_i\right] = \frac{\omega_i(\vartheta)}{2}\phi^2 \sigma^2_{z_i|s_i}. \tag{A.12}$$

Using the expressions for the prior and posterior entropy provided in (4) to transform equation (A.11) leads to

$$\kappa_i = \frac{1}{2}\log_2\left(\frac{\sigma^2_{z_i}}{\sigma^2_{z_i|s_i}}\right),$$

which means that

$$\sigma^2_{z_i|s_i} = \sigma^2_{z_i}\, 2^{-2\kappa_i}. \tag{A.13}$$

Using these two results, the optimization problem given by (A.7)-(A.11) can be written as

$$\max_{\kappa_A,\kappa_N \geq 0} \quad \sum_{i\in\{A,N\}} u_i^*(\vartheta) - \frac{\omega_i(\vartheta)}{2}\phi^2\sigma_{z_i}^2\, 2^{-2\kappa_i} - \sum_{i\in\{A,N\}} \mu_i\kappa_i \tag{A.14}$$

Taking the derivative with respect to κ_i yields the first-order condition

$$\{\kappa_i\}: \quad \omega_i(\vartheta)\phi^2\sigma_{z_i}^2\, 2^{-2\kappa_i}\ln(2) = \mu_i. \tag{A.15}$$

Solving for κ_i leads to the result

$$\kappa_i^* = \begin{cases} \frac{1}{2}\log_2\left(\frac{\omega_i(\vartheta)\phi_i^2\sigma_{z_i}^2\ln(2)}{\mu_i}\right) & \text{if } \frac{\omega_i(\vartheta)\phi_i^2\sigma_{z_i}^2\ln(2)}{\mu_i} \geq 1 \\ 0 & \text{else} \end{cases} \tag{A.16}$$

The numerator of the term inside the logarithm is the marginal increase in utility associated with paying attention. The denominator, μ_i, is the marginal cost of attention. The farmer will only devote a positive amount of attention to domain i if the marginal benefit at $\kappa = 0$ exceeds the marginal cost. For a concave utility function with the assumed properties, it holds that the marginal utility of additional payoff is higher at lower levels of utility. Therefore, a negative shock to payoff, either in the agricultural or the non-agricultural domain, will shift the farmer to a part of the utility function where $\omega_i(\vartheta)$ takes a larger value, causing κ_A^* to increase (since the model is symmetric in the two domains, the same effects also applies to κ_N^*). In the same way, it follows from equation (A.16) that κ_A^* will be larger with more costly mistakes (i.e., $\omega_A \uparrow$ for reasons other than shocks ϑ), larger prior uncertainty about the optimal action ($\phi_A^2\sigma_{z_A}^2 \uparrow$), and a smaller cost of being attentive to the agricultural domain ($\mu_A \downarrow$).

B Data and variables

The data in our source, the World Bank's LSMS-ISA database, are collected in collaboration with the national statistics offices of the participating countries in Sub-Saharan Africa, often building upon existing surveys on agriculture in these countries. While the LSMS-ISA project seeks to provide information in a comparable manner across countries, the survey designs sometimes involve considerable differences in the type of collected information and the way questions are asked. As far as possible, we restrict our analysis to variables for which the available information is comparable across countries. The following provides additional information on the construction of variables and handling of the unique survey design in each country. For more details on the data collection process and utilized tools, we refer to the original survey documents and enumerator manuals

available at World Bank (2018).

Agricultural seasons. For countries with two cropping seasons within a year (Malawi and Uganda), we focus our analysis only on the main season. In Nigeria, the survey in each season is split into two visits (post-planting and post-harvest), and some of the information is collected separately for the time "since the new year" (first visit) and "since the last interview" (second visit). In computing variables over one agricultural season, we combine the information from these two visits (e.g., the number of extension contacts is calculated as the sum of reported contacts across both visits).

Local currencies and units of measurement. For all countries, local currencies are transformed into US dollars using yearly average exchange rates from the World Development Indicator database. Information on quantities and area that was collected based on local units of measurement is transformed into standard units by using (as far as available) the conversion factors provided in the LSMS-ISA database.

Plots and farm size. All surveys collect data on plot areas based both on farmer-reported values and GPS measurement. In Malawi and Nigeria, the data are collected at the plot level. In Uganda, the corresponding unit of observation is called parcel (we follow the approach of other authors and aggregate information across plots belonging to the same parcel; see Sheahan and Barrett, 2017). For our analysis, we use GPS measures as the main basis. Since GPS estimates are not available for all plots (e.g., due to flooding, security concerns, or because plots are located too far away from the household), we complement the data with farmer-reported plot areas where necessary. The variable *Cultivated Area* (which we use both in the construction of other variables and as a dependent variable itself), includes only plots which are cultivated by the household in a given season (i.e., excluding fallow, pasture, and forest land, as well as plots that are given or rented out by the household).

Perceived quality of received advice. The information in Table 1 on whether received advice was rated as useful by farmers was obtained as follows. In all surveys, farmers are asked to rate the quality of the advice received. In Malawi and Nigeria, the question is stated as "how useful was the advice/information received?". In Uganda, the corresponding question is "How would you rate the advice received?". The underlying scales differ between countries. To make farmers' responses comparable across countries, we classified responses into two categories: "useful or very useful" and "useless or bad". The former category comprises the responses "useful" and "very useful" in Malawi, "somewhat useful" and "very useful" in Nigeria, and "average" and "good" in Uganda. Responses grouped together as "useless or bad" are "not very useful" and "useless" in Malawi, "not

very useful", "not useful", and "harmful" in Nigeria, and "bad" in Uganda.

Use of modern farm inputs. All surveys collect data on used seeds, fertilizer, agrochemicals (mainly pesticides and herbicides), and irrigation. However, the exact information differs between countries and, in some instances, between different survey rounds of the same country. This applies particularly to the data on improved seed varieties, where most of the earlier survey rounds do not allow us to distinguish between different types of seeds. Therefore, our indicator variable for improved seeds is only available for a subset of survey rounds. For fertilizer, agrochemicals, manure, and irrigation we observe binary input use decisions at the plot level, i.e., whether farmers used the respective input (in any quantity) on individual plots or parcels. Based on this plot-level information, the household indicators which we use in the analysis are set equal to one if farmers report having used the respective input on at least one plot during a given season.

For seeds, fertilizer and agrochemicals we also observe used quantities. The corresponding household-level variables are obtained by summing up reported quantities across individual plots belonging to a household. In addition, we also observe the costs farmers incurred for these three inputs, including costs for purchasing, transportation to the farm, and obtaining input coupons (in Malawi). In most surveys, data on incurred costs are only available for inputs which have been purchased in the same season. In these cases, we use the available data to calculate country- and wave-specific prices for each input, which we then use to assign values to those inputs which are reported to be left over from the previous season.

Farm output and productivity. The variable *Harvest* is based on farmer-reported estimates of the value of harvested crops for individual plots. In Nigeria, farmers are asked directly what would have been the total value of their harvested crops, if everything had been sold at current market prices. In Malawi and Uganda, the total value of harvest is based on separate data about harvested quantities and prices of sold crops. The latter is used to calculate country- and wave-specific median market prices for each individual crop, which are then used to assign monetary values to farmers' harvests. This approach is used because many farmers sell only a small fraction of their harvested quantities of a given crop, and it is not clear whether they could have sold the remaining (unsold) produce for the same price.

Agricultural productivity (*Harvest per ha*) is computed by dividing, for each plot, the value of harvest by cultivated area, and then calculating the weighted average at the household level using plot areas as weights. In addition, we also observe quantities and values of a number of farm inputs. We use these data to construct a proxy for farmers' profits, namely *Net Harvest*, which captures farmers' total value of harvest net of the

estimated value of used seeds, fertilizer, and agrochemicals.

Farm labor input. We observe the amount of labor input provided by family members as well as the incurred costs for hired labor. The latter is based on household-specific information about average daily wages paid, number of hired persons, and number of days for which laborers were hired. To capture the cost for both types of labor in a single variable (*Cost Labor*), we use the information on costs for hired labor to calculate country-wave median wages for two categories (harvest and non-harvest activities), which we then use to assign a monetary value to provided family labor (i.e., assuming the same wage for family labor as for hired labor for each category). We do not account for differences in the composition of hired or family labor with respect to gender and age (i.e., adults or children).

Table A1: List of variables

Variable	Full sample[a]	Malawi	Nigeria	Uganda	Description[b]
HH characteristics:					
Adults	2.89	2.61	3.25	2.79	Number of adults in HH
Children	2.90	2.51	2.98	3.16	Number of children in HH
Education (head)					Educational level of HH head
No schooling	0.26	0.17	0.40	0.20	D: Never attended school
Primary educ.	0.51	0.60	0.35	0.59	D: Primary or Quranic school
Secondary educ.	0.23	0.23	0.24	0.21	D: Secondary education or more
Age head	47.8	43.6	51.9	47.2	Age of HH head (years)
Male head	0.78	0.76	0.87	0.70	D: HH head is male
Farm outcomes:					
Harvest	502.0	289.6	882.1	308.7	Value of harvest (USD)
Net Harvest	433.6	228.7	750.4	295.8	Value of harvest net of input costs (USD)
Production choices:					
Cultivated Area	1.35	1.12	1.18	1.70	Total cultivated plot area (hectare)
Fertilizer	0.40	0.79	0.42	0.04	D: HH uses inorganic fertilizer
Agrochemicals	0.19	0.05	0.40	0.11	D: HH uses agrochemicals
Improved Seeds	0.33	0.56	0.17	0.18	D: HH uses improved seeds
Manure	0.15	0.22	0.11	0.12	D: HH uses organic fertilizer
Irrigation	0.02	0.01	0.03	0.02	D: HH uses irrigation
Qty. Fertilizer	67.5	96.5	108.8	1.9	Quantity of used fertilizer (kg)
Qty. Agrochem.	2.7	1.8	5.5	0.7	Quantity of used agrochemicals (kg)
Cost Fertilizer	30.1	41.4	48.9	1.9	Value of used fertilizer (USD)
Cost Agrochem.	8.8	2.9	20.7	1.8	Value of used agrochemicals (USD)
Cost Seeds	28.8	15.8	59.5	9.1	Value of used seeds (USD)
Cost Labor	281.8	107.6	552.6	170.2	Value of family and hired labor (USD)
Extension:					
Advice	0.34	0.63	0.19	0.26	D: Received advice in past year
Extension	0.29	0.47	0.17	0.26	D: Received advice (excl. media)
Solicited Extension	0.20	0.35	0.12	0.15	D: Actively requested advice
Contacts	1.12	1.58	0.88	1.03	Number of extension contacts
Solicited Contacts	0.81	1.25	0.53	0.78	Number of actively requested contacts
Shocks:					
AgShock	0.43	0.82	0.12	0.41	D: Agricultural shock in past year
NonAgShock	0.22	0.40	0.14	0.16	D: Non-agricultural shock in past year
Observations (max.)	25,274	7,519	8,874	8,881	

Notes: Numbers are mean values. Only households with at least one cultivated plot are included. [a]The full sample is obtained by pooling data across countries and waves. [b]"D:" indicates dummy variables. Local currencies are transformed into US dollars using yearly average exchange rates from the World Development Indicator database. *Source:* Authors' calculation based on survey data from the LSMS-ISA database (World Bank, 2018). Included survey rounds are: Malawi (2010-11, 2013-14, 2016-17), Nigeria (2010-11, 2012-13, 2015-16), and Uganda (2009-10, 2010-11, 2011-12, 2013-14).

Table A2: Exposure to agricultural advice by country and survey round

Description	Malawi			Nigeria			Uganda			
	wave 1	wave 2	wave 3	wave 1	wave 2	wave 3	wave 1	wave 2	wave 3	wave 4
HHs who received agricultural advice (%)	32.1	47.0	69.0	16.9	13.4	19.7	34.9	21.9	28.1	21.0
of those:										
avg. number of contacts	3.7	4.4	3.9	5.3	6.2	4.9	5.0	4.4	3.1	3.8
more than 2 contacts (%)	50.1	56.0	50.0	56.5	63.2	63.2	46.8	47.2	36.2	34.9
more than 10 contacts (%)	4.6	6.5	5.3	12.0	17.6	9.4	11.8	13.2	6.4	5.8
received advice rated as useful or very useful[a] (%)	44.6	91.6	91.9	86.9	87.5	97.9	88.9	78.0	87.0	92.8
received advice rated as useless or bad[a] (%)	7.0	9.7	8.9	5.8	2.3	1.8	7.5	10.6	13.4	8.4
paid in order to receive advice (%)	0.9	1.1	0.7	10.6	22.2	12.1	19.0	18.0	10.7	6.6
HHs who actively solicited advice (%)	26.1	36.9	49.5	11.5	10.8	14.9	22.4	11.9	15.5	12.4
Share of solicited contacts (%)	80.6	82.5	78.0	60.6	70.3	62.9	75.5	74.0	78.4	75.1
Observations	2,592	3,029	1,601	3,072	2,925	2,847	1,833	2,080	2,158	2,389

Notes: Agricultural advice measures in-person advice and excludes advice received through media (TV, radio, flyers, etc.). [a]Exact wording differs between countries (see Appendix B). *Source:* Authors' calculation based on survey data from the LSMS-ISA database (World Bank, 2018).

Table A3: Sources of advice by country and survey round

Description[a]	Malawi			Nigeria			Uganda			
	wave 1	wave 2	wave 3	wave 1	wave 2	wave 3	wave 1	wave 2	wave 3	wave 4
Government extension service	49.3	43.9	32.3	27.5	16.2	18.9	78.6	86.4	93.7	86.7
Private extension service, input supplier	1.9	2.7	2.6	9.8	11.6	13.4	7.5	2.0	1.8	4.4
NGO, lead farmer and farmer field day/school	9.1	12.9	8.7	5.1	11.0	13.2	17.5	12.5	7.6	12.7
Farmer cooperative/association	1.8	1.7	1.0	5.3	1.6	4.0	7.2	5.5	1.0	4.6
Other farmer (neighbor, relative, large-scale)	11.6	19.1	34.2	46.9	51.4	55.1	4.7	1.1	0.3	1.2
Village agricultural extension meeting	6.9	8.2	4.3	5.9	5.9	12.7				
Media (TV, radio, flyers)	40.7	53.8	35.8	23.5	25.8	15.6				
Other	1.9	2.8	1.4	4.3	3.9	3.0	7.5	5.7	1.3	2.6
Observations (HHs who received advice)	1,119	1,966	1,429	510	438	597	640	455	606	502

Notes: Numbers are percentages of households who received advice from indicated source, conditional on having received any advice. [a]Exact wording differs between countries. *Source:* Authors' calculation based on survey data from the LSMS-ISA database (World Bank, 2018).

Table A4: Mean values of household characteristics across households with different (transitory) shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				No	With	With transition in:		
	No shock	With AgShock	With NonAgShock	transition in shocks	transition in shocks	AgShock	NonAgShock	Both shocks
Adults	3.02	2.79	2.86	2.86	2.92	2.91	2.91	2.89
Children	2.76	2.96	2.88	2.68	3.05	3.17	2.95	3.10
Primary educ.	0.41	0.57	0.54	0.48	0.53	0.53	0.54	0.55
Secondary educ.	0.26	0.21	0.22	0.24	0.21	0.22	0.20	0.20
Age head	50.03	46.34	47.34	47.41	48.08	47.87	48.45	48.39
Male head	0.82	0.75	0.76	0.79	0.76	0.77	0.75	0.76
HH-Wave Obs.	6,545	15,737	10,804	10,647	14,134	9,486	9,042	4,394
Households	3,152	6,805	4,504	6,085	4,893	3,168	3,171	1,446
P-value (H_0: *Demeaned* values are jointly equal to *demeaned* values in column (4)[a])					0.099	0.130	0.511	0.835
P-value (H_0: *Demeaned* values are jointly equal to *demeaned* values in column (1)[a])					0.563	0.394	0.682	0.895

Notes: Columns show mean values for subsets of households as follows. Column (1): households without any reported shock across all survey rounds, (2): households with at least one agricultural shock across survey rounds, (3): households with at least one nonagricultural shock across survey rounds, (4): households without transition in any shock, (5): households with at least one transition in *AgShock* or Non*AgShock*, (6): households with transition in *AgShock*, (7): households with transition in *NonAgshock*, (8): households with transitions in both *AgShock* and *NonAgshock*. [a] The last two rows report p-values for joint F-tests on the equality of demeaned values across the subset of households included in the corresponding column and those included in column (4) and column (1), respectively, using wild cluster bootstrap standard errors (10,000 repetitions) at the stratum level (consisting of 24 clusters defined as region×rural). Demeaned values are demeaned taking the mean of the respective variable at the household level over up to four waves. For details on the construction of *AgShock* and *NonAgshock*, see Table 3.

C Robustness of tests of model predictions

Table A5: Test of model predictions: Robustness to different ways of clustering

	(1) Advice	(2) Advice	(3) Advice	(4) Extension	(5) Extension	(6) Extension	(7) Solicited Extension	(8) Solicited Extension	(9) Solicited Extension
AgShock	0.087*	0.087***	0.087***	0.072*	0.072***	0.072***	0.061**	0.061***	0.061***
	(0.098)	(0.000)	(0.004)	(0.084)	(0.000)	(0.004)	(0.039)	(0.000)	(0.000)
NonAgShock	0.033*	0.033***	0.033***	0.030*	0.030**	0.030***	0.025*	0.025**	0.025***
	(0.096)	(0.007)	(0.006)	(0.078)	(0.020)	(0.008)	(0.058)	(0.025)	(0.002)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes
Cluster[a]	2-way	district	wild	2-way	district	wild	2-way	district	wild
Observations	20,392	20,392	20,392	20,392	20,392	20,392	19,653	19,653	19,653

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. [a] Clusters and associated numbers of clusters are as follows: "district" (158); "2-way": stratum (24) × wave (up to 4); "wild": wild bootstrap (1,000 repetitions) for stratum (24). As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

Table A6: Test of model predictions: Robustness to alternative variable definitions

	(1) Extension (no peers)	(2) Extension	(3) Extension	(4) Sol. Exten. (no peers)	(5) Solicited Extension	(6) Solicited Extension
AgShock	0.053***	0.067***		0.055***	0.056***	
	(0.004)	(0.002)		(0.001)	(0.001)	
NonAgShock	0.030**		0.031**	0.020**		0.025***
	(0.016)		(0.025)	(0.022)		(0.007)
NonAgShock (incl. food)		0.041***			0.041***	
		(0.007)			(0.000)	
AgShock (incl. food)			0.064***			0.059***
			(0.003)			(0.000)
HH FE	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Observations	20,391	20,392	20,392	20,260	19,653	19,653
R-squared (within)	0.020	0.034	0.033	0.018	0.027	0.026

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

Table A7: Test of model predictions: Robustness to exclusion of HH fixed effects

	(1) Advice	(2) Advice	(3) Advice	(4) Advice	(5) Advice	(6) Advice	(7) Advice	(8) Advice
AgShock	0.252***	0.252**	0.252**	0.252***	0.250***	0.250**	0.250**	0.250***
	(0.001)	(0.016)	(0.035)	(0.000)	(0.000)	(0.014)	(0.031)	(0.000)
NonAgShock	0.095***	0.095***	0.095**	0.095***	0.095***	0.095***	0.095**	0.095***
	(0.000)	(0.000)	(0.042)	(0.000)	(0.000)	(0.000)	(0.046)	(0.000)
Adults					0.013**	0.013*	0.013	0.013***
					(0.032)	(0.054)	(0.102)	(0.000)
Children					0.002	0.002	0.002	0.002
					(0.606)	(0.654)	(0.602)	(0.515)
Primary educ. (head)					0.031	0.031	0.031	0.031
					(0.497)	(0.638)	(0.519)	(0.312)
Second. educ. (head)					0.051	0.051	0.051	0.051
					(0.277)	(0.448)	(0.327)	(0.128)
Age head					-0.001	-0.001	-0.001	-0.001
					(0.665)	(0.632)	(0.713)	(0.657)
Age head sq.					-0.000	-0.000	-0.000	-0.000
					(0.570)	(0.526)	(0.611)	(0.573)
Male head					0.031	0.031	0.031	0.031
					(0.192)	(0.262)	(0.274)	(0.120)
HH FE	no	no	no	no	no	no	no	no
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes
Cluster[a]	stratum	wild	2-way	district	stratum	wild	2-way	district
Observations	20,392	20,392	20,392	20,392	20,392	20,392	20,392	20,392
R-squared	0.090	0.090	0.090	0.090	0.101	0.101	0.101	0.101

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. [a] Clusters and associated numbers of clusters are as follows: "stratum" (24); "wild": wild bootstrap (1,000 repetitions) for stratum (24); "2-way": stratum (24) × wave (up to 4); "district" (158). The omitted category for education is "no schooling".

Table A8: Test of model predictions: Disaggregated topics of advice

	(1) Agric. prod. & processing	(2) Marketing & crop sales	(3) Livestock production	(4) Animal diseases & vaccination	(5) Fishery	(6) Forestry	(7) Access to credit
AgShock	0.069***	0.038***	0.034**	0.031***	-0.004	0.023**	0.009**
	(0.002)	(0.001)	(0.022)	(0.006)	(0.671)	(0.035)	(0.038)
NonAgShock	0.027**	0.010	0.022	0.017*	-0.003	0.014	0.001
	(0.022)	(0.446)	(0.123)	(0.096)	(0.611)	(0.372)	(0.961)
HH FE	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes
Observations	20,351	20,350	20,350	20,350	20,350	13,697[a]	13,697[a]
R-squared (within)	0.033	0.016	0.029	0.020	0.015	0.033	0.028
Mean dep. var.	0.254	0.072	0.095	0.087	0.023	0.044	0.036

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). The dependent variables are only equal to one if the household actively requested advice. [a]Numbers of observations in columns (6) and (7) are smaller, because the categories "Forestry" and "Access to credit" are not available in Uganda (see list of topics of advice in Table 2). As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

Table A9: Placebo test

	(1) Unsolicited Extension	(2) Unsolicited Extension	(3) Unsolicited Extension
AgShock	0.004	0.004	0.003
	(0.579)	(0.612)	(0.715)
NonAgShock	0.007	0.007	0.007
	(0.344)	(0.336)	(0.360)
Adults		-0.000	
		(0.828)	
Children		0.001	
		(0.708)	
Primary educ. (head)		0.008	
		(0.307)	
Second. educ. (head)		-0.010	
		(0.534)	
Age head		-0.001	
		(0.717)	
Age head sq.		0.000	
		(0.597)	
Male head		0.006	
		(0.671)	
HH FE	yes	yes	yes
Wave FE	yes	yes	yes
Full set of control dummies			yes
Observations	20,392	20,392	20,392
R-squared (within)	0.003	0.004	0.012

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). The omitted category for education is "no schooling". Full sets of control dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

D The relation between agricultural advice, input choices, and farm outcomes

This appendix investigates the association between demand-driven advisory services and farm decisions and outcomes. For this purpose, we estimate a number of regressions of the form

$$y_{it} = \beta_0 + \beta_1 Extension_{it} + \beta_2 AgShock_{it} + \beta_3 X_{it} + \mu_i + \omega_t + \epsilon_{it}, \tag{D.1}$$

where the dependent variables we consider belong to one of the two following groups. In the first group are measures of farm performance, such as total value of harvest, value of harvest per hectare, and value of harvest net of input costs. Second, we are interested in specific channels through which provided agricultural advice may affect these outcomes. In investigating potential channels, we focus on the link between extension services and farmers' decisions related to the amount of cultivated land, allocation of labor, and use of modern farm inputs.

For this analysis we use our observational data, and unobserved factors will likely be correlated with both exposure to extension services and outcomes.[31] Relative to most existing work based on observational data (see Birkhaeuser et al., 1991; Evenson, 2001; Benin et al., 2011), the panel structure of our dataset allows us to make some progress towards dealing with endogeneity, by making it possible to control for unobserved time-invariant household characteristics via the included household fixed effects. Further, we can also control to some extent for time varying unobservables by including indicators of agricultural shocks incurred by households. Finally, we also include a number of time varying household characteristics which are likely to be important (e.g., household size and education). Nevertheless, we stress that our ability to make causal claims is limited.

To measure farm performance, the dataset contains information about the total value of harvested crops (estimated by farmers) and about the incurred costs for inputs, including seeds, fertilizer, and other agrochemicals (see Appendix B for details on how these costs are calculated). This information is used to construct a measure of agricultural productivity (value of harvest per hectare of cultivated land) and a proxy for farmers' profits (defined as the value of harvest net of the estimated value of used seeds, fertilizer, and agrochemicals). As potential channels, we investigate the effect of extension services on the size of cultivated land, allocation of labor, and farmers' decision to adopt modern agricultural input technologies. Regarding the latter, we focus on use of improved seed

[31] The dominant view in the literature seems to be that simple OLS estimates of the effects of extension on farm outcomes tend to be biased upward, as more productive farmers also have more exposure to extension services (Birkhaeuser et al., 1991; Evenson, 2001).

varieties, inorganic fertilizer, and other agrochemicals (pesticides, herbicides, etc.).[32] In addition to binary indicators for use of individual modern inputs in a given season, we also observe the applied quantities of fertilizer and agrochemicals. In order to limit the influence of outliers, most of our regressions involving farm outputs or input costs use logarithmic transformations of the original values as dependent variables. In addition, in some specifications (indicated in the notes to tables) we exclude outliers that we identify as those observations for which either value of harvest or net value of harvest per hectare is in the top or bottom 1% of the distribution.

Table A10 reports estimates for the regression model specified in equation (D.1), both with and without including non-agricultural shocks. For both specifications, results are obtained for two different outcome variables. In the first five columns, the dependent variable is the logarithm of farmer-reported total value of harvest. In the second half of the table, the dependent variable is the logarithm of value of harvest net of input costs (including costs for seeds, fertilizer, and agrochemicals).[33]

The estimates in Table A10 show a consistently positive correlation between the two outcome variables and indicators of received extension services. In all specifications, the coefficients of the extension variables are statistically significant. The quantitative role of extension services suggested by these estimates seems reasonable: Receiving (solicited) agricultural advice is associated with a 7% larger value of harvest and 8% higher value of harvest net of input costs.

We note that the coefficient for *NonAgShock* does not change much once the extension variable is included. This suggests that the direct effect of the non-agricultural shocks on seeking advice is, although statistically significant, small in absolute magnitude. In addition, the fact that there are significant effects of non-agricultural shocks on input choices (see Tables A12 and A13 below), even after controlling for extension seeking behavior, highlights a previously not mentioned implication of the theory. Theory also predicts that other actions that bring high returns but need attention receive more attention in response to a non-agricultural shock. This may include using modern inputs (without asking for advice). Therefore, the fact that non-agricultural shocks predict input use is also consistent with the theory.

Furthermore, we find that the sizes of the coefficients for the extension variables are considerably larger when we do not control for unobserved household characteristics using fixed effects (not shown here). This suggests an upward bias in simple OLS estimates caused by positive selection of more productive farmers into extension programs, which

[32]Information on improved seeds is only available for a subset of survey rounds, since most of the earlier LSMS-ISA surveys do not distinguish between different types of seeds.

[33]Note that after dropping outliers as described in the text, of the logarithmic dependent variables used in Tables A10 and A12, only "cost of inputs" and "cost of labor" have remaining zeros. To be able to include observations with zero costs, we take the logarithms after adding 0.01 to the original variables. This transformation affects 2,500 observations in Table A12, columns (1) to (5), and 79 observations in columns (6) to (10), respectively.

Table A10: Extension and farm outcomes

	log(Harvest)					log(Net Harvest)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AgShock	-0.078**	-0.082**	-0.083***	-0.081**	-0.082**	-0.081**	-0.086**	-0.086**	-0.085**	-0.086**
	(0.017)	(0.013)	(0.010)	(0.015)	(0.011)	(0.029)	(0.022)	(0.019)	(0.023)	(0.019)
NonAgShock	0.019		0.016		0.017	0.010		0.008		0.008
	(0.526)		(0.578)		(0.555)	(0.735)		(0.801)		(0.779)
Extension		0.079***	0.078***				0.079***	0.078***		
		(0.001)	(0.001)				(0.007)	(0.007)		
Solicited Extension				0.068***	0.067***				0.083**	0.083**
				(0.006)	(0.006)				(0.020)	(0.019)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	18,112	18,112	18,112	18,112	18,112	17,483	17,483	17,483	17,483	17,483
R-squared (within)	0.028	0.029	0.029	0.029	0.029	0.025	0.026	0.026	0.026	0.026

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). Outliers are excluded as explained in the text. As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

coincides with the perception in the literature described above (see footnote 31). As an aside, note that the agricultural shock variable is indeed significantly negatively correlated with harvest value in Table A10, which confirms the usefulness of this (self-reported) shock variable for the above analysis.

There are several possible channels through which extension services may affect farm outcomes. First, it may be the case that access to advice simply motivates farmers to cultivate more land. In this case, total value of harvest would tend to increase, while productivity (i.e., harvest per unit of land) might remain unaffected. Second, extension services may indeed help farmers to achieve higher productivity. An important channel through which this may be accomplished is by facilitating the adoption and use of modern farm inputs, such as improved seed varieties, fertilizer, and pesticides, which are known to be an important factor in determining agricultural productivity (Evenson and Gollin, 2003; Morris et al., 2007; Duflo et al., 2011).

Tables A11 and A12 present estimation results which suggest that particularly the latter channel through use of modern inputs may be at work. According to the results in columns (2) to (5) of Table A11, farmers who receive extension do not tend to cultivate more (or less) land.[34] At the same time, these farmers are able to generate 53 to 58 dollars in additional harvest value per hectare of land, an increase of 6 to 7% relative to the mean (columns 7 to 10).

As can be seen in columns (2) to (5) of Table A12, farmers who receive advice spend more money on modern farm inputs (the included costs are for seeds, fertilizer, and agrochemicals). This may be seen as in line with the figures reported in Table 2, which show that a large share of the provided advice from extension services is related to agricultural input use. Finally, columns (7) to (10) of Table A12 suggest that extension services are not significantly associated with the amount of labor farmers allocate to their plots (including both family and hired labor).

Tables A13 and A14 provide further insights into the link between extension and modern input use. As shown in the first four columns of Table A13, receiving advice through extension is associated with a slight increase in the number of agricultural inputs used (considered inputs are improved seeds, irrigation, manure, fertilizer, and agrochemicals). When looking at binary adoption decisions for individual inputs, improved seeds, fertilizer, and agrochemicals show significant coefficients. For fertilizer and agrochemicals, we also observe applied quantities (Table A14). While the coefficients are not always statistically significant, they are generally positive and of plausible magnitude. Overall, the results in Tables A11, A12, A13, and A14 are in line with the view that extension services can have positive effects on farmers' productivity by increasing the use of modern farm inputs.

[34] In the data, cultivated area changes frequently over time, which may be explained by the large share of plots which farmers report to rent or use for free.

Table A11: Extension and production choices (Part 1)

	Cultivated Area (in ha)					Harvest per ha (US$)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AgShock	-0.136	-0.105	-0.139	-0.100	-0.134	-127.360*	-135.291**	-131.667**	-135.104**	-131.476**
	(0.585)	(0.670)	(0.579)	(0.683)	(0.589)	(0.051)	(0.043)	(0.046)	(0.043)	(0.046)
NonAgShock	0.562		0.561		0.563	-58.779*		-61.453*		-60.792*
	(0.131)		(0.136)		(0.133)	(0.066)		(0.056)		(0.060)
Extension		0.058	0.040				53.129**	56.036**		
		(0.747)	(0.831)				(0.046)	(0.037)		
Solicited Exten.				-0.019	-0.037				55.188**	57.717**
				(0.918)	(0.850)				(0.049)	(0.044)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	18,652	18,652	18,652	18,652	18,652	14,893	14,893	14,893	14,893	14,893
R-squared (within)	0.023	0.023	0.023	0.023	0.023	0.023	0.023	0.024	0.023	0.024
Mean dep. var.	1.40	1.40	1.40	1.40	1.40	871.13	871.13	871.13	871.13	871.13

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). Outliers are excluded as explained in the text. Local currencies are transformed into US dollars using yearly average exchange rates from the World Development Indicator database. As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

Table A12: Extension and production choices (Part 2)

	log(Cost Inputs)					log(Cost Labor)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AgShock	0.255*	0.242*	0.235	0.246*	0.238*	-0.063	-0.058	-0.060	-0.062	-0.064
	(0.079)	(0.091)	(0.102)	(0.088)	(0.099)	(0.511)	(0.536)	(0.520)	(0.510)	(0.495)
NonAgShock	0.127**		0.117**		0.120**	0.030		0.031		0.030
	(0.020)		(0.025)		(0.023)	(0.431)		(0.391)		(0.421)
Extension		0.300***	0.296***				-0.047	-0.048		
		(0.001)	(0.001)				(0.489)	(0.473)		
Solicited Exten.				0.270***	0.266***				0.011	0.011
				(0.001)	(0.001)				(0.868)	(0.878)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	18,680	18,680	18,680	18,680	18,680	18,385	18,385	18,385	18,385	18,385
R-squared (within)	0.033	0.035	0.035	0.034	0.034	0.132	0.132	0.132	0.131	0.132

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). Logarithms are obtained after adding 0.01 to the original variables. Outliers are excluded as explained in the text. Local currencies are transformed into US dollars using yearly average exchange rates from the World Development Indicator database. As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

Table A13: Extension and modern input use (Part 1)

	Number of Inputs				Improved Seeds				Irrigation				Manure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AgShock	0.019	0.016	0.019	0.016	-0.017	-0.018	-0.017	-0.018	0.001	0.001	0.001	0.001	0.030*	0.028*	0.029*	0.027*
	(0.529)	(0.599)	(0.514)	(0.584)	(0.120)	(0.112)	(0.124)	(0.114)	(0.643)	(0.668)	(0.629)	(0.656)	(0.070)	(0.090)	(0.076)	(0.096)
NonAgShock		0.051**		0.052**		0.014**		0.015***		0.001		0.001		0.033***		0.033***
		(0.020)		(0.019)		(0.010)		(0.005)		(0.820)		(0.816)		(0.009)		(0.009)
Extension	0.113**	0.111**			0.040**	0.039**			-0.000	-0.000			0.019	0.018		
	(0.014)	(0.015)			(0.038)	(0.040)			(0.968)	(0.962)			(0.284)	(0.307)		
Solicited Exten.			0.112**	0.110**			0.042**	0.041**			-0.001	-0.001			0.028	0.027
			(0.017)	(0.017)			(0.038)	(0.040)			(0.869)	(0.863)			(0.118)	(0.129)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	18,693	18,693	18,693	18,693	13,469	13,469	13,469	13,469	18,545	18,545	18,545	18,545	18,609	18,609	18,609	18,609
R-squared (within)	0.070	0.070	0.069	0.070	0.023	0.023	0.023	0.023	0.016	0.016	0.016	0.016	0.078	0.079	0.078	0.079
Mean dep. var.	1.015	1.015	1.015	1.015	0.318	0.318	0.318	0.318	0.022	0.022	0.022	0.022	0.148	0.148	0.148	0.148

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). Logarithms are obtained after adding 0.01 to the original variables. Outliers are excluded as explained in the text. As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

Table A14: Extension and modern input use (Part 2)

	Fertilizer: Any				Fertilizer: log(Quantity)				Agrochemicals: Any				Agrochemicals: log(Quantity)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AgShock	-0.002	-0.003	-0.002	-0.002	-0.058	-0.059	-0.058	-0.059	-0.001	-0.001	0.000	-0.000	0.001	-0.004	0.005	0.000
	(0.854)	(0.848)	(0.872)	(0.865)	(0.646)	(0.640)	(0.644)	(0.638)	(0.962)	(0.926)	(0.984)	(0.978)	(0.990)	(0.944)	(0.930)	(0.998)
NonAgShock		0.001		0.001		0.008		0.009		0.008		0.009		0.079*		0.082*
		(0.892)		(0.870)		(0.901)		(0.891)		(0.259)		(0.230)		(0.063)		(0.053)
Extension	0.023***	0.023***			0.179***	0.179**			0.039**	0.039**			0.249**	0.247**		
	(0.002)	(0.003)			(0.009)	(0.010)			(0.032)	(0.033)			(0.039)	(0.041)		
Solicited Exten.			0.020**	0.020**			0.192**	0.192*			0.031	0.030			0.203	0.200
			(0.020)	(0.022)			(0.049)	(0.052)			(0.152)	(0.153)			(0.137)	(0.140)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	18,620	18,620	18,620	18,620	18,589	18,589	18,589	18,589	18,665	18,665	18,665	18,665	18,631	18,631	18,631	18,631
R-squared (within)	0.015	0.015	0.014	0.014	0.014	0.014	0.014	0.014	0.023	0.023	0.022	0.022	0.025	0.025	0.024	0.024
Mean dep. var.	0.399	0.399	0.399	0.399					0.219	0.219	0.219	0.219				

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors are clustered at the stratum level (consisting of 24 clusters defined as region×rural). Logarithms are obtained after adding 0.01 to the original variables. Outliers are excluded as explained in the text. As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

Robustness. Table A15 tests the robustness of the link between extension and farm outcomes (as reported in Table A10 above) with respect to clustering and handling of missing observations. In particular the data on harvest values contains many observations where information is missing for some individual plots or crops within households. In the analysis so far, these cases have been treated as zero when summing up over all crops and plots of a household. The results in Table A15 show that the link between extension and farm outcomes remains significant when the analysis is restricted to those households for which information on harvest is complete (i.e., available for all crops and all plots).

Table A16 repeats a similar exercise for the link between extension and farmers' production choices (as reported in Tables A11 and A12). The dependent variables *Cultivated Area* and *Harvest per ha* are based on the amount of cultivated area, which (similar to the data on harvest) involves missing values for individual plots within households. The results in columns (1) to (8) in Table A16 show that excluding households for which this is the case leads to similar coefficients as before, though significance levels in columns (5) to (8) drop. As a result, the coefficients of the extension variables in these columns become slightly insignificant (with p-values around 0.13). For all other estimates which have previously been significant, the results remain significant at least at the 10% significance level.

Table A17 tests the robustness of the link between extension and use of modern farm inputs (as reported in Tables A13 and A14) with respect to two-way clustering of standard errors. As significance levels tend to become smaller, only some of the coefficients for extension remain statistically significant. In particular, the results in Table A17 show that the coefficients for extension and solicited extension remain statistically significant at the 10% level for use of improved seeds and fertilizer, whereas the results for agrochemicals become insignificant.

Table A15: Extension and farm outcomes: Robustness

	log(Harvest)								log(Net Harvest)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AgShock	-0.114***	-0.115***	-0.114**	-0.115**	-0.113***	-0.114***	-0.113**	-0.114**	-0.102**	-0.101**	-0.102*	-0.101*	-0.102**	-0.101**	-0.102	-0.101*
	(0.002)	(0.001)	(0.036)	(0.028)	(0.002)	(0.001)	(0.039)	(0.030)	(0.024)	(0.021)	(0.096)	(0.085)	(0.024)	(0.020)	(0.101)	(0.090)
NonAgShock		0.008		0.008		0.009		0.009		-0.007		-0.007		-0.007		-0.007
		(0.802)		(0.848)		(0.802)		(0.849)		(0.862)		(0.892)		(0.855)		(0.888)
Extension	0.105***	0.104***	0.105**	0.104**					0.128***	0.128***	0.128**	0.128**				
	(0.000)	(0.000)	(0.013)	(0.014)					(0.000)	(0.000)	(0.027)	(0.028)				
Solicited Exten.					0.098***	0.098***	0.098**	0.098**					0.138***	0.138***	0.138**	0.138**
					(0.000)	(0.000)	(0.019)	(0.020)					(0.000)	(0.000)	(0.011)	(0.011)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample restr.[a]	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Clusters	stratum	stratum	2-way	2-way	stratum	stratum	2-way	2-way	stratum	stratum	2-way	2-way	stratum	stratum	2-way	2-way
Observations	13,648	13,648	13,648	13,648	13,648	13,648	13,648	13,648	13,199	13,199	13,199	13,199	13,199	13,199	13,199	13,199

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Standard errors clustered at the stratum level consist of 24 clusters defined as region×rural. Two-way ("2-way") clusters are defined as stratum (24) × wave (up to 4). Outliers are excluded as explained in the text. [a]Observations are dropped if information on harvest involves missings. As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

Table A16: Extension and production choices: Robustness

	Cultivated Area (in ha)				Harvest per ha (US$)				log(Cost Inputs)				log(Cost Labor)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AgShock	-0.144	-0.178	-0.139	-0.174	-132.819	-128.563	-132.578	-128.311	0.242	0.235	0.246	0.238	-0.058	-0.060	-0.062	-0.064
	(0.577)	(0.496)	(0.587)	(0.504)	(0.128)	(0.134)	(0.130)	(0.136)	(0.169)	(0.178)	(0.169)	(0.177)	(0.569)	(0.555)	(0.543)	(0.530)
NonAgShock		0.581		0.583		-74.128**		-73.436**		0.117		0.120		0.031		0.030
		(0.165)		(0.164)		(0.041)		(0.038)		(0.153)		(0.148)		(0.500)		(0.523)
Extension	0.121	0.103			52.594	56.132			0.300*	0.296*			-0.047	-0.048		
	(0.412)	(0.504)			(0.126)	(0.125)			(0.051)	(0.051)			(0.510)	(0.500)		
Solicited Exten.			0.060	0.042			53.639	56.754			0.270**	0.266**			0.011	0.011
			(0.677)	(0.787)			(0.134)	(0.134)			(0.045)	(0.046)			(0.880)	(0.890)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sample restr.[a]	yes	yes	yes	yes	yes	yes	yes	yes								
Cluster	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way
Observations	18,415	18,415	18,415	18,415	14,722	14,722	14,722	14,722	18,680	18,680	18,680	18,680	18,385	18,385	18,385	18,385

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Two-way ("2-way") clusters are defined as stratum (24 entities based on region×rural) × wave (up to 4). Logarithms are obtained after adding 0.01 to the original variables. Outliers are excluded as explained in the text. [a]Observations are dropped if information on cultivated area involves missings. Local currencies are transformed into US dollars using yearly average exchange rates from the World Development Indicator database. As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

Table A17: Extension and modern input use: Robustness

	Improved Seeds		Fertilizer: Any		Fertilizer: log(Quantity)		Agrochemicals: Any		Agrochemicals: log(Quantity)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AgShock	-0.018	-0.018	-0.003	-0.002	-0.059	-0.059	-0.001	-0.000	-0.004	0.000
	(0.474)	(0.478)	(0.848)	(0.866)	(0.616)	(0.616)	(0.921)	(0.976)	(0.945)	(0.998)
NonAgShock	0.014***	0.015***	0.001	0.001	0.008	0.009	0.008	0.009	0.079	0.082
	(0.010)	(0.006)	(0.848)	(0.822)	(0.855)	(0.850)	(0.284)	(0.266)	(0.133)	(0.126)
Extension	0.039*		0.023**		0.179*		0.039		0.247	
	(0.092)		(0.044)		(0.060)		(0.122)		(0.131)	
Solicited Exten.		0.041*		0.020*		0.192*		0.030		0.200
		(0.077)		(0.067)		(0.094)		(0.204)		(0.196)
HHFE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Cluster	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way
Observations	13,469	13,469	18,620	18,620	18,589	18,589	18,665	18,665	18,631	18,631

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Two-way ("2-way") clusters are defined as stratum (24 entities based on region×rural) × wave (up to 4). Logarithms are obtained after adding 0.01 to the original variables. Outliers are excluded as explained in the text. As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.