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

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Abstract

Low levels of investment into technologies, and more generally, limited use of measures that have low cost but appear to have high returns, present a puzzle to observers of economic development. This paper investigates one such puzzling observation, namely the relatively low demand for agricultural advisory services, which have modest (most frequently zero) monetary cost but are estimated to result in large increases of profits. We propose a model that can explain this observation, and show empirical results based on detailed data from Sub-Saharan Africa that are consistent with predictions of this model. Building on rational inattention theory, we model farmers as rational decision makers facing scarce attention. Agricultural 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. The empirical results are in line with central predictions of the model. We also use our data to provide empirical support for the model's assumption that advisory services have positive effects on production.

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 (Morris et al., 2007; Jama and Pizarro, 2008; World Bank, 2008). One puzzle is that farmers do not make us of measures that have relatively low costs but high returns. In particular, modern farm inputs, such as fertilizer and improved seeds, are frequently not adopted despite demonstrated high expected returns, and, conditional on adoption, inputs are used in suboptimal amounts. The literature proposes a number of arguments for why this is the case. These include market imperfections related to finance, insurance, and quality control (Moser and Barrett, 2006; Dercon and Christiaensen, 2011; Karlan et al., 2014; Bold et al., 2017), individual and social learning (Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Conley and Udry, 2010; Hanna et al., 2014), limited attention and other informational frictions (Cole and Fernando, 2013; Casaburi et al., 2014; Naeher, 2018), 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.

Based in part on some of these findings, the provision of agricultural extension (i.e., agricultural advisory and consulting services) is a major policy instrument that is used to overcome the underlying constraints, especially those related to information and attention. According to Feder (2005) and Anderson and Feder (2007), there are nearly one million agricultural extension workers worldwide, of which 90% are located in developing countries. In addition to traditional forms of agricultural extension, which are primarily based on field visits by extension staff to farm households, modern advisory services also include the provision of information through the use of model farmers (Bandiera et al., 2017) and approaches driven by information and communication technology (ICT), such as agricultural apps, consulting hotlines, and SMS-based reminders (Aker, 2011; Cole and Fernando, 2013; Casaburi et al., 2014). More efforts to overcome the underlying constraints, especially those related to informational constraints, are currently under way, e.g., the 'Netflix for Agriculture' initiative by Fabregas et al. (2017).

Despite the wide use of extension services by policy makers and NGOs, relatively little is known about them. An important question is why extension services are not demanded more widely by farmers. 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 extension-based advice despite apparently high returns (Evenson, 2001; Cole and Fernando, 2013; Casaburi et al., 2014) is particularly puzzling in light of the low costs of extension services.[1]

[1]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

This paper uses a rational inattention model to contribute to a better understanding of the apparent puzzle of relatively modest usage of low-cost advisory services despite high expected returns. We show that farmers may rationally decide not to participate in extension programs if (i) requesting, implementing, and benefiting from agricultural advice requires farmers to be attentive, and (ii) attention is a scarce resource. One of the predictions of the model is that shocks that are not directly related to agriculture but have negative effects on farmers' income or wealth (such as theft of money), will increase the probability that farmers demand agricultural advice. This prediction helps us to distinguish the identified channel in the model from other theories that are commonly used in the literature to explain suboptimal farm decisions and outcomes. Relying on detailed farm-level data on shocks (both related and unrelated to agriculture) and the use of extension services from Sub-Saharan Africa, we then demonstrate that empirical observations are consistent with the prediction of the proposed rational inattention model. Taking into account both theoretical considerations and additional empirical insights, we further argue that other prominent theories in this context, e.g., based on learning or resource constraints, are unable to account for this feature of the data. To complement our main analysis, we also provide empirical support for the model's assumption that advisory services have a positive effect on production. To this end, we use our data to establish a positive correlation between demand-driven extension services and farm decisions and outcomes, focusing on the role of advisory services in facilitating adoption and usage of modern farm inputs, such as improved seed varieties and fertilizer. Various features of our data allow us to improve upon prior literature that also uses observational data to study the effects of extension services, but we stress that the observational nature of the data limits our ability to make causal claims.

The model we propose for studying farmers' demand for advice centers around the idea that farmers (like anybody else) face a limited capacity to attend to information, which causes attention to be a costly resource.[2] 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 this feature, we model household decision making in two domains, agriculture and non-agriculture. One particular theoretical result, which we will use to distinguish this model from other models, is that shocks in the non-agricultural domain may increase demand for extension. The intuition is as follows. In the model, agricultural

95% (84% of district-years), which suggests that extension services are widely available in the countries we study.

[2]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).

advisory services are available to farmers free of charge and farmers expect a positive effect on their production when participating in such programs. Absorbing provided advice and implementing the activities suggested by extension workers, however, requires attention, which is a scarce 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. The modeling insights are more broadly applicable and the empirical support for the model provided in this paper suggest that scarce attention may be part of explanations for phenomena in economic development beyond the specific application studied here.

The empirical work is based on survey data from the Living Standard Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) database (World Bank, 2016), which provides household-level information on the use of extension services, agricultural production, and various types of shocks.[3] We first show that empirical findings are in line with the theoretical predictions of the model. 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). The data further allow us to measure the use of extension services, and, crucially, to separately identify extension services that are actively requested by farmers from unsolicited extension services of which the household is merely a passive recipient. There is statistically strong and very robust evidence that, in line with the model, non-agricultural shocks indeed increase farmers' demand for agricultural advice. In addition, we assess the plausibility of some alternative explanations which might also account for the observed link, but do not find strong evidence in favor of those alternative explanations.

Our model assumes that agricultural advice does indeed have positive effects on production. We therefore also investigate the relation between agricultural advice and farm decisions and outcomes. In particular, we investigate the role that demand-driven extension services play in determining farmers' input decisions and associated farm outcomes in our data. The panel structure of the LSMS-ISA data allows us to make some progress in addressing the endogeneity problems facing existing studies in this context (see the survey papers provided by Birkhaeuser et al., 1991; Evenson, 2001). 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 agricul-

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

tural advice is associated with a 7% larger value of harvest and 8% higher profits. 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 known to be important determinants of agricultural productivity (Evenson and Gollin, 2003; Morris et al., 2007; Duflo et al., 2011).

Our paper contributes to several different literatures. First, we add to the growing body of literature that studies attentional constraints to decision making (Banerjee and Mullainathan, 2008; DellaVigna, 2009; Maćkowiak and Wiederholt, 2009; Beaman et al., 2014; Hanna et al., 2014; Bartoš et al., 2016). 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).[4] In this paper, we follow the literature on rational inattention, which assumes that people allocate their attention optimally across different pieces of information, incorporating the costs associated with acquiring and processing information (Sims, 2003; Maćkowiak and Wiederholt, 2009; Matějka and McKay, 2015). In contrast to other models with limited attention, which impose an exogenous signal structure on the decision maker, the rational inattention literature uses an entropy-based approach to quantify information and attention, and allows agents to freely choose the distribution from which signals are drawn. This offers a possibility to endogenize not only the quantity, but also the structure of information (for a more detailed overview and discussion of different approaches to attention used in economics see Handel and Schwartzstein, 2018). Until now, the literature on rational inattention has focused primarily on applications in rich countries.[5] 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.

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 infor-

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

[5]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 consider applications in the areas of finance (Van Nieuwerburgh and Veldkamp, 2010; Kacperczyk et al., 2016), industrial organization (Sallee, 2014; Martin, 2017), and labor (Acharya and Wee, 2016; Bartoš et al., 2016).

mation 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 electricity 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. While some of these related papers have highlighted the role of scarce mental resources in productivity (e.g., Banerjee and Mullainathan, 2008), the present paper suggests a specific channel through which limited attention affects productivity, and provides empirical support for this channel.[6]

Second, we add to the recent literature in development economics that tries to explain low levels of technology adoption and low input use in agriculture, in particular in Sub-Saharan Africa (Dercon and Christiaensen, 2011; Duflo et al., 2011; Suri, 2011; Bold et al., 2017). Third, we also contribute to the policy debate about the determinants and constraints of the use of extension services and their returns (Rivera and Alex, 2005; Davis, 2008; Benin et al., 2011; Cole and Fernando, 2013; Casaburi et al., 2014). 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.

The remainder of the paper is organized as follows. Section 2 provides further background on agricultural extension services. Section 3 presents the model and derives predictions about farmers' demand for agricultural advice. Section 4 tests the predictions of the model and provides empirical evidence on the role of extension services in determining farmers' input decisions and resulting production outcomes. Section 5 concludes.

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.

[6] Note that what is termed "attention" in the literature usually comprises both cognitive effort and time use in general (our model is no exception to that). However, as pointed out by Banerjee and Mullainathan (2008), the relevant aspect of time use in this context must be thought of as the "quality of time (i.e., attention)" rather than the "quantity of time" (p. 493).

Many 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).

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[7] 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).[8]

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.[9]

Despite the prominence of demand-driven agricultural extension programs on the current agenda of many international development organizations, little quantitative evidence exists about the impact and returns of advice that is provided at farmers' request. According to Evenson (2001), empirical studies that focus on estimating the impact of agricultural extension services using observational data can be grouped into two categories, based on the level at which extension is observed. The first are studies that use farm-specific variables to capture extension at the household level, such as the number

[7]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).

[8]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).

[9]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).

of visits or contacts between extension staff and individual farm households. With observational data, such approaches likely face endogeneity concerns.[10] Attempts to apply instrumental variable techniques or panel data methods to deal with these issues are very sparse, due to data limitations and the difficulty of finding suitable instruments (Evenson, 2001; Benin et al., 2011). The recently collected dataset that we use allows us to address some of these issues in ways that help to obtain more credible estimates on the effects of extension services. In addition, existing studies in the literature usually work with extension variables that do not distinguish between visits that were initiated by the demand or the supply side. In contrast, we are able to separately identify extension contacts that are actively demanded by farmers.

The second group of empirical work identified by Evenson (2001) comprises studies that are based on information for defined extension regions (i.e., not farm-specific). Typically, these data are used to create measures of "extension services supplied", which are then assigned to each farm observation in the respective regions (e.g., per-farm-extension spending in a region, or a dummy variable indicating the presence of an extension agent at the village level). While this can help to address endogeneity problems resulting from some forms of selection, papers that follow this approach are by construction focusing on the supply side of extension and are thus unsuited to provide insights about demand-driven forms of extension.

Finally, there are some recent studies that quantify impacts of agricultural extension using RCTs (Cole and Fernando, 2013; Casaburi et al., 2014). While such studies can provide valuable insights about the causal effects and returns of agricultural advisory services, the obtained results are typically based on very specific groups of farmers and relatively limited sampling frames. Our analysis seeks to complement the findings of these studies by providing evidence from nationally representative samples of farmers in Sub-Saharan Africa.

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, as well as (ii) why non-agricultural shocks can increase farmers' demand for agricultural advice and participation in extension services. The model builds upon the following main assumptions. First, farmers

[10] One particular concern is that more productive farmers are more inclined to seek additional information through advisory services, which likely creates an upward bias if this selection is not controlled for. Further, a bias can be due to selection on the supply side: extension agents may tend to contact farmers more frequently based on characteristics that are also determinants of farm performance measures. Selection on characteristics such as having better social networks or living in closer proximity to towns is likely to induce an upward bias. Of course, there are also plausible arguments for downward biases.

have access to some sources of agricultural advice (e.g., extension services), and engaging with these sources has a positive effect on production. Second, requesting and benefiting from 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.[11]

3.1 Model

We study the decision problem of a farmer who faces choice problems in two distinct domains. The first domain (in the following referred to as 'agricultural' domain) captures decisions in the farmer's production process that are related to, e.g., crop types, usage of inputs, and other agricultural tasks. The second domain ('non-agricultural') captures all other decisions which require the farmer's attention, e.g., how to deal with the sickness or death of a household member. For each domain, the farmer's decisions are summarized in a single action $a_i \in \mathbb{R}$, where $i \in \{A, N\}$ denotes the agricultural domain (A) or non-agricultural domain (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 a fundamental of the economy that is initially unobserved by the farmer (e.g., current prices, demand for certain crops, and soil conditions).[12] Choosing a suboptimal action $a_i \neq a_i^*$ reduces the maximal payoff $\overline{u}_i^*$ associated with domain i. For example, in the agricultural domain this may correspond to using the wrong type or quantity of pesticide given the current conditions described by the realization of z_A.

In addition, there may be exogenous events ϑ_i that directly reduce the payoff for a_i (e.g., theft of money or lost harvest). In contrast to z_i, these shocks cannot be compensated for by selecting appropriate actions. Therefore, any realization of ϑ_i unequal to zero induces a direct shift in the level of utility. The highest possible payoff in each domain is thus given by

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

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

[12] The analysis is restricted to the case where fundamentals are independent across domains, which implies that 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 (e.g., advisory services) and thereby reduce the uncertainty about 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.[13] In particular, paying attention to z_i is modeled as receiving a noisy signal

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

where $\epsilon_i \sim \mathcal{N}(0, \sigma_{\epsilon_i}^2)$.[14] 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 given by

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

Based on these definitions, the amount of attention devoted to the choice problem associated with a_i is described by

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

This means that the more attention is devoted to a_i, the better the quality of the acquired signal, and thus the larger the possible reduction in uncertainty about the fundamental z_i and associated optimal action a_i^*.[15]

Capturing the idea that attention is a scarce resource, the farmer faces in each domain the cost $\mu_i \kappa_i$. The unit cost of attention $\mu_i > 0$ 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 and education).

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

[13] 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). 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).

[14] 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.

[15] Notice that this differs from standard models in economics, which typically 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).

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:

$$\max_{a_i \in \mathbb{R}} \quad E\left[u\left(a_i, z_i, \vartheta\right)|s_i\right], \tag{6}$$

where $\vartheta = (\vartheta_A + \vartheta_N)$. Let $\hat{a}_i$ denote the optimal action 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. The corresponding solution to the farmer's optimization problem is derived in Appendix A. Based on the resulting optimal allocation of attention, the model gives rise to a number of predictions, which are formalized in the following two propositions.

Proposition 1. *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 1 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.

Furthermore, the comparative statics of the model lead to several predictions about the role of attention-related factors in determining farmers' demand for agricultural advice, summarized in the following proposition.

Proposition 2. *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. □

It should be noted that while the implications in Proposition 2 are exclusively based on parameters associated with the agricultural domain itself, the results in Proposition 1 also involve parameters of the non-agricultural domain. These cross-domain effects arise from the overarching utility function in the farmer's objective, which connects both domains through the channel of imperfect attention.

Discussion. In the case of agricultural shocks, the predicted effect in Proposition 1 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 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 (e.g., illness of a household member). This prediction holds, as long as these shocks do not affect optimal cultivation practices (e.g., because shocks to health can be compensated by hired labor, leaving optimal cultivation practices and other agricultural decisions unchanged).

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), which implies that optimal decisions in the agricultural domain may be affected by non-agricultural shocks. This would be the case if, for example, 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 unable 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 provided free of charge.

Both of these questions can be answered based on a model with costly attention. In addition, one may think of other channels through which non-agricultural shocks might be linked to demand for extension (e.g., based on a combination of learning and market imperfections). Therefore, in addition to testing the predictions of the model, the empirical part below also addresses some alternative theories in this context.

4 Empirical evidence

This section empirically tests the predictions of the model and provides evidence on the role of extension services in determining farmers' input decisions and resulting production outcomes.

4.1 Data and descriptive statistics

The analysis 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). 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).[16] We focus on households that engage in agricul-

[16]Detailed information about the design and implementation of the surveys in each country can be found at World Bank (2016). While the LSMS-ISA database covers more countries, only data from the three countries we use here offer the information we need for our analysis (e.g., to distinguish solicited from unsolicited advice).

tural activities and report having cultivated at least one plot in a given season.[17] This leaves us with a maximum of 25,274 household-wave observations, based on 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 households with missing information on their use of agricultural advice, those with missing data on shocks, and those 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 20,392 household-wave observations. The following provides a brief description of the key variables used to test the model's predictions.[18]

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.

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 agricultural advice through extension. In Malawi (which generates 32% of its GDP in the agricultural sector and is known for its relatively strong policy focus on agriculture, see 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 through extension services rate the received advice as

[17] For countries with two cropping seasons (Malawi and Uganda), we focus our analysis on the main season.

[18] Additional information on the construction of variables and differences in survey designs across countries can be found in Appendix B. A complete list of all included variables, together with basic summary statistics, is provided in Table A1.

Table 1: Exposure to agricultural advice

Description	Full Sample	Malawi	Nigeria	Uganda
Households who received agricultural advice (%)	28.7	46.5	16.7	26.0
of those:				
avg. 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 actively solicited advice (%)	19.5	35.0	12.4	15.3
Share of solicited 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, 2016).

useful, and less than 10% of farmers report having received advice that was useless. On average, less than 8% of households that received extension services paid anything for them.[19]

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.

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. The latter is collected based on a list of around 20 different events, which are similar across countries. To test the predictions of the model, we

[19]Conditional on paying for extension services, 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, 2016).

classify shocks as either directly related to agriculture (*AgShock*) or not directly related to agriculture (*NonAgShock*). 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 or other valuables", and "end of regular assistance/remittances". A list of the shock categories that appear in the data and the assigned categories for the baseline regressions is provided in Table A4 in the appendix. We exclude the category "other" from our analysis. The shock category "increase in the prices for food" is not classified in our baseline regressions and we explore alternative classifications as part of the robustness tests.[20]

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, highest educational level obtained by any household member (*educ.max*), as well as educational level, age, and gender of the household head.

[20]As can be seen in Table A4, the extent to which households report experiencing negative shocks differs considerably between countries. The same applies to different survey rounds within countries, although to a smaller degree. For example, in Nigeria only 10 to 13% of farmers report having been negatively affected by agricultural shocks, while in Malawi and Uganda the percentage is never below 60 and 30, respectively. During the 2010-11 season (wave 1) in Malawi, less than 2% of farmers report the end of receiving remittances or assistance from outside the household. In waves 2 and 3, the number increases to 11% and 16%, respectively.

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 1). 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 2). Therefore, we expect household characteristics such as education and household size to be correlated with farmers' demand for extension.

Table 3 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 further restricted to solicited advice, i.e., the dummy is only equal to one if the household actively requested advice. The results in Table 3 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 in Section 4.5 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 3 as being in line with the predictions of the model (as described in Proposition 1) and providing empirical support for the suggested limited attention channel.

Table 3: Test of model predictions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Advice	Advice	Advice	Extension	Extension	Extension	Solicited Extension	Solicited Extension	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

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.

Furthermore, the results in columns (2), (5), and (8) of Table 3 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.[21] 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 of the household head, nor for the highest educational level of any household member. 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.

One may be worried about the role of individual components of the aggregate non-agricultural shock measure. Therefore, in Table 4 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 4 repeats the estimation results from the main specification (column 9 in Table 3). In column (2), only shocks related to health are used to construct the non-agricultural shock dummy variable. The health dummy is further disaggregated into two individual shock items in column (3). Columns (4) to (7) repeat the same approach for shocks related to income and crime. In column (8), all three types of non-agricultural shocks are included simultaneously. Overall, the results in Table 4 indicate that the link between non-agricultural shocks and farmers' demand for extension is statistically robust, even for separate categories of non-agricultural shocks.

4.3 Discussion of alternative interpretations

One concern in testing 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 might be the case if adverse shocks to households' wealth or income would also lead to changes in the optimal level of modern agricultural input use (e.g., because farmers have imperfect access to credit), or if optimal farm decisions are sensitive to shocks that affect the availability of family labor (see Section 3.2).

[21]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 a sample of maize farmers in Kenya.

Table 4: Test of model predictions: Disaggregated shocks

	(1) Solicited Extension	(2) Solicited Extension	(3) Solicited Extension	(4) Solicited Extension	(5) Solicited Extension	(6) Solicited Extension	(7) Solicited Extension	(8) Solicited Extension
AgShock	0.061***	0.063***	0.062***	0.061***	0.046**	0.062***	0.061***	0.060***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.038)	(0.001)	(0.001)	(0.001)
NonAgShock	0.025***							
	(0.007)							
NonAgShock(Health)		0.022**						0.017*
		(0.030)						(0.066)
Illness or accident of HH member			0.025*					
			(0.088)					
Death or disability of HH member			0.030					
			(0.172)					
NonAgShock(Income)				0.055***				0.049**
				(0.008)				(0.013)
Loss of employment					0.013			
					(0.901)			
Reduction in non-farm income					-0.009			
					(0.681)			
End of assistance/remittances					0.112***			
					(0.003)			
NonAgShock(Crime)						0.046**		0.041**
						(0.020)		(0.041)
Theft of money/valuables							0.058**	
							(0.025)	
Conflict/violence							0.034*	
							(0.089)	
HH FE	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Observations	19,653	19,653	19,653	19,653	13,063[a]	19,653	19,653	19,653
R-squared (within)	0.026	0.025	0.026	0.026	0.036	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 category "End of assistance/remittance" is not available in Uganda (see list of shock items in Table A4). As controls, full sets of dummies are included for the following variables: adults, children, education of HH head, age of head, male head.

In order to assess whether this is likely to be the case, Table A5 in the appendix explores the link between shocks and farmers' demand for extension using disaggregated advice topics. 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).

Furthermore, when we investigate the relationship between receiving advice and farmers' production choices, we do not find evidence of a significant link between the amount of labor farmers allocate to their plots (including both family and hired labor) and participation in extension services (see Table 6 in Section 4.4). Thus, there seems to be no support for the concern that non-agricultural shocks may affect farmers' demand for extension by creating a need for advice on optimal farm practices with respect to labor inputs.

Finally, one might 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 nonagricultural shocks.

4.4 Role of demand-driven agricultural advice

We now turn to investigating the role of demand-driven advisory services in determining farm decisions and outcomes. For this purpose, we estimate a number of regressions of the form

$$y_{it} = \beta_0 + \beta_1 Extension_{it} + \beta_2 AgShock_{it} + \beta_3 X_{it} + \mu_i + \omega_t + \epsilon_{it}, \tag{10}$$

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, harvest per hectare, and realized profits (i.e., 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.

Note again that we work with observational data, and unobserved factors will likely be correlated with both exposure to extension services and outcomes. 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 (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 also include a number of time varying household characteristics which are likely to be important (e.g., household size and education), as well as indicators of shocks incurred by households. 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), as well as the incurred costs for inputs (including seeds, fertilizer, and other agrochemicals). This information is used to calculate a measure of agricultural productivity (value of harvest per hectare of cultivated land) and farmers' profits (value of harvest net of input costs). 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 varieties, inorganic fertilizer, and other agrochemicals (pesticides, herbicides, etc.).[22] 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 profit per hectare is in the top or bottom 1% of the distribution.

Table 5 reports estimates for both the full regression model specified in equation (10), and for the case where no household fixed effects are included. For both specifications, results are obtained for two different outcome variables. In the first four 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 realized profits.[23]

The estimates in Table 5 show a consistently positive correlation between the two outcome variables and indicators of received extension services. With the exception of column (5), all coefficients are statistically significant. The quantitative role of extension services suggested by these estimates seems reasonable. According to the results reported in even-numbered columns, which control for household fixed effects, receiving agricultural

[22]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.

[23]Note that after dropping outliers as described in the text, of the logarithmic dependent variables used in Tables 5 and 6, 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 6, columns (5) and (6), and 79 observations in columns (7) and (8), respectively.

Table 5: Extension and farm outcomes

	(1) log(Harv)	(2) log(Harv)	(3) log(Harv)	(4) log(Harv)	(5) log(Profit)	(6) log(Profit)	(7) log(Profit)	(8) log(Profit)
AgShock	-0.485***	-0.084***	-0.485***	-0.081**	-0.510***	-0.084**	-0.509***	-0.085**
	(0.000)	(0.009)	(0.000)	(0.015)	(0.000)	(0.019)	(0.000)	(0.023)
Extension	0.105	0.066***			0.079	0.075**		
	(0.131)	(0.003)			(0.274)	(0.013)		
Sol. Exten.			0.213**	0.068***			0.185**	0.083**
			(0.016)	(0.006)			(0.036)	(0.020)
HH FE		yes		yes		yes		yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Observations	18,803	18,803	18,112	18,112	18,133	18,133	17,483	17,483
R-squared	0.198		0.200		0.175		0.177	
R-squared (within)		0.028		0.029		0.025		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.

advice from extension services is associated with a 7% larger value of harvest and 8% higher profits. Furthermore, Table 5 shows that the size of the coefficients is considerably smaller when controlling for unobserved household characteristics using fixed effects. This suggests an upward bias in simple OLS estimates caused by positive selection of more productive farmers into extension programs, which coincides with the perception in the literature described above. As an aside, note that the agricultural shock variable is indeed significantly negatively correlated with harvest and profits, 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).

Table 6 presents estimation results which suggest that particularly the latter channel through use of modern inputs may be at work. According to the results in columns (1)

Table 6: Extension and production choices

	(1) Cult. Area (in ha)	(2) Cult. Area (in ha)	(3) Harvest per ha (US$)	(4) Harvest per ha (US$)	(5) log(Cost Inputs)	(6) log(Cost Inputs)	(7) log(Cost Labor)	(8) log(Cost Labor)
AgShock	-0.096	-0.100	-131.931**	-135.104**	0.226	0.246*	-0.073	-0.062
	(0.680)	(0.683)	(0.049)	(0.043)	(0.113)	(0.088)	(0.437)	(0.510)
Extension	0.082		63.152**		0.237***		-0.101	
	(0.573)		(0.034)		(0.004)		(0.207)	
Sol. Exten.		-0.019		55.188**		0.270***		0.011
		(0.918)		(0.049)		(0.001)		(0.868)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Observations	19,361	18,652	15,524	14,893	19,391	18,680	19,092	18,385
R-squared (within)	0.022	0.023	0.022	0.023	0.032	0.034	0.122	0.131
Mean dep. var.	1.38	1.40	851.8	871.1				

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.

and (2), farmers who receive extension do not tend to cultivate more (or less) land.[24] At the same time, these farmers are able to generate 55 to 63 dollars in additional harvest value per hectare of land, an increase of 6 to 7% relative to the mean (columns 3 and 4). As can be seen in columns (5) and (6), 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) and (8) of Table 6 suggest that extension services are not significantly associated with the amount of labor farmers allocate to their plots (including both family and hired labor).

Table 7 provides further insights into the link between extension and modern input use. As shown in the first two columns, 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 have information on the quantities applied by farmers. While the coefficients are not always statistically

[24] 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.

significant, they are generally positive and of plausible magnitude. Overall, the results in Tables 6 and 7 are in line with the view that extension services can have positive effects on farmers' productivity by increasing the use of modern agricultural input technologies.

4.5 Robustness of econometric results

Additional robustness checks with respect to clustering of standard errors, variable definitions, and handling of outliers and missing values are reported in Appendix C. As shown in Table A6, the model predictions hold when standard errors are clustered along both stratum and wave dimensions ("2-way"), as well as when clustered at the district level (there are 158 districts). Table A7 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 A8 tests the robustness of the link between extension and farm outcomes (as reported in Table 5) 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 A8 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 A9 repeats a similar exercise for the link between extension and farmers' production choices (see Table 6). The dependent variables in the first four columns 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 (4) in Table A9 show that excluding households for which this is the case leads to similar coefficients as before, though significance levels in columns (3) and (4) drop. As a result, the coefficient of solicited extension in column (4) becomes slightly insignificant (with a p-value of 0.13). For all other estimates which have previously been significant, the results remain significant at least at the 10% significance level.

Table A10 tests the robustness of the link between extension and use of modern farm inputs (see Table 7) with respect to two-way clustering of standard errors. As significance levels tend to become smaller, only some of the coefficients for solicited extension remain statistically significant, while the *Extension* indicator (which includes both solicited and unsolicited advice) becomes generally insignificant. In particular, the results in columns

Table 7: Extension and modern input use

	Number of Inputs		Improved Seeds		Irrigation		Manure		Fertilizer				Agrochemicals			
									Any	Any	log(Qty)	log(Qty)	Any	Any	log(Qty)	log(Qty)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AgShock	0.015	0.019	-0.015	-0.017	0.002	0.001	0.031**	0.029*	-0.005	-0.002	-0.083	-0.058	-0.002	0.000	-0.010	0.005
	(0.594)	(0.514)	(0.129)	(0.124)	(0.445)	(0.629)	(0.044)	(0.076)	(0.684)	(0.872)	(0.505)	(0.644)	(0.825)	(0.984)	(0.865)	(0.930)
Extension	0.086*		0.033		0.001		0.016		0.014*		0.107		0.031*		0.202*	
	(0.079)		(0.106)		(0.810)		(0.338)		(0.072)		(0.107)		(0.064)		(0.063)	
Sol. Exten.		0.112**		0.042**		-0.001		0.028		0.020**		0.192**		0.031		0.203
		(0.017)		(0.038)		(0.869)		(0.118)		(0.020)		(0.049)		(0.152)		(0.137)
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	19,404	18,693	14,132	13,469	19,254	18,545	19,319	18,609	19,331	18,620	19,298	18,589	19,376	18,665	19,342	18,631
R-squared (within)	0.062	0.069	0.019	0.023	0.015	0.016	0.076	0.078	0.013	0.014	0.013	0.014	0.022	0.022	0.024	0.024
Mean dep. var.	1.031	1.015	0.327	0.318	0.022	0.022	0.152	0.148	0.409	0.399			0.213	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$\times$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.

(2), (4), and (6) of Table A10 show that the coefficients for solicited extension remain statistically significant at the 10% level for use of improved seeds and fertilizer.

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 are not directly related to farming (e.g., theft of money or non-farm business failure), and thus do not constitute an immediate reason for farmers to request agricultural advice.

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.

We test the predictions of the model empirically, and – consistent with the theoretical prediction that is specific to the model of this paper – we find statistically strong evidence for the predicted link between non-agricultural shocks and farmers' demand for agricultural advice. 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.

To complement our main analysis, we also use our data to provide empirical support for the model's assumption of a positive link between extension services and farmers' input decisions and achieved outcomes. Using the LSMS-ISA panel data we find that receiving agricultural advice is associated with significantly larger farm output and productivity, as well as with higher use of modern agricultural input technologies. While we are able to control for household fixed effects and various time-varying observables (including farm characteristics and shocks), we stress that concerns about endogeneity remain.

Overall, our findings suggest 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. This highlights 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.

References

Acharya, S. and S. L. Wee (2016). Rational inattention in hiring decisions. Unpublished working paper.

Aker, J. C. (2011). Dial "A" for agriculture: A review of information and communication technologies for agricultural extension in developing countries. *Agricultural Economics 42*(6), 631–647.

Anderson, J. R. (2007). Agricultural advisory services. *Background paper for the World Development Report 2008*.

Anderson, J. R. and G. Feder (2007). Agricultural extension. *Handbook of Agricultural Economics 3*, 2343–2378.

Bandiera, O., R. Burgess, E. Deserrano, I. Rasul, and M. Sulaiman (2017). Women farmers and barriers to technology adoption in rural Uganda. Work in progress, description available at: ww.povertyactionlab.org/evaluation/women-farmers-and-barriers-technology-adoption-rural-uganda.

Bandiera, O. and I. Rasul (2006). Social networks and technology adoption in Northern Mozambique. *Economic Journal 116*(514), 869–902.

Banerjee, A. and S. Mullainathan (2008). Limited attention and income distribution. *American Economic Review 98*(2), 489–493.

Bardhan, P. and C. Udry (1999). *Development Microeconomics*. Oxford University Press.

Bartoš, V., M. Bauer, J. Chytilová, and F. Matějka (2016). Attention discrimination: Theory and field experiments with monitoring information acquisition. *American Economic Review 106*(6), 1437–1475.

Beaman, L., J. Magruder, and J. Robinson (2014). Minding small change among small firms in Kenya. *Journal of Development Economics 108*(2014), 69–86.

Benin, S., E. Nkonya, G. Okecho, J. Randriamamonjy, E. Kato, G. Lubade, and M. Kyotalimye (2011). Returns to spending on agricultural extension: The case of the National Agricultural Advisory Services (NAADS) program of Uganda. *Agricultural Economics 42*(2), 249–267.

Bick, A., N. Fuchs-Schündeln, and D. Lagakos (2018). How do hours worked vary with income? Cross-country evidence and implications. *American Economic Review 108*(1), 170–99.

Birkhaeuser, D., R. Evenson, and G. Feder (1991). The economic impact of agricultural extension: A review. *Economic Development and Cultural Change 39*(3), 607–650.

Birner, R. and J. R. Anderson (2007). How to make agricultural extension demand-driven? The case of India's agricultural extension policy. *IFPRI Discussion Paper 729*.

Bold, T., K. Kaizzi, J. Svensson, and D. Yanagizawa-Drott (2017). Lemon technologies and adoption: Measurement, theory and evidence from agricultural markets in Uganda. *Quarterly Journal of Economics 132*(3), 1055–1100.

Bordalo, P., N. Gennaioli, and A. Shleifer (2013). Salience and consumer choice. *Journal of Political Economy 121*(5), 803–843.

Caplin, A. and M. Dean (2013). Rational inattention and state dependent stochastic choice. Unpublished working paper.

Casaburi, L., M. Kremer, S. Mullainathan, and R. Ramrattan (2014). Harnessing ICT to increase agricultural production: Evidence from Kenya. Unpublished working paper.

Chipeta, S. (2006). *Demand Driven Agricultural Advisory Services.* Neuchâtel Group, Lindau.

Cole, S. and A. N. Fernando (2013). The value of advice: Evidence from mobile phone-based agricultural extension. Unpublished working paper.

Conley, T. G. and C. R. Udry (2010). Learning about a new technology: Pineapple in Ghana. *American Economic Review 100*(1), 35–69.

Davis, K. E. (2008). Extension in Sub-Saharan Africa: Overview and assessment of past and current models, and future prospects. *Journal of International Agricultural and Extension Education 15*(3), 15–28.

Deininger, K., S. Savastano, and F. Xia (2017). Smallholders' land access in Sub-Saharan Africa: A new landscape? *Food Policy 67*, 78–92.

DellaVigna, S. (2009). Psychology and economics: Evidence from the field. *Journal of Economic Literature 47*(2), 315–372.

Dercon, S. (2002). Income risk, coping strategies, and safety nets. *World Bank Research Observer 17*(2), 141–166.

Dercon, S. and L. Christiaensen (2011). Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. *Journal of Development Economics 96*(2), 159–173.

Duflo, E., M. Kremer, and J. Robinson (2011). Nudging farmers to use fertilizer: Theory and experimental evidence from Kenya. *American Economic Review 101*(6), 2350–2390.

Evenson, R. and D. Gollin (2003). Assessing the impact of the Green Revolution, 1960 to 2000. *Science 300*(5620), 758–762.

Evenson, R. E. (2001). Economic impacts of agricultural research and extension. *Handbook of Agricultural Economics 1*, 573–628.

Fabregas, R., M. Kremer, J. Robinson, and F. Schilbach (2017). Netflix for agriculture. Work in progress, URL: https://www.atai-research.org/wp-content/uploads/2017/06/Netflix-for-Agriculture-Prof.-Michael-Kremer.pdf.

FAO (2014). *The state of food and agriculture: Innovation in family farming.* Food and Agriculture Organization of the United Nations, Rome.

Feder, G. (2005). The challenges facing agricultural extension - and a new opportunity. *New Agriculturalist*. Available at: www.new-ag.info/en/view/point.php?a=1253.

Foster, A. D. and M. R. Rosenzweig (1995). Learning by doing and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy 103*(6), 1176–1209.

Gabaix, X., D. Laibson, G. Moloche, and S. Weinberg (2006). Costly information acquisition: Experimental analysis of a boundedly rational model. *American Economic Review 96*(4), 1043–1068.

Gido, E. O., K. W. Sibiko, O. I. Ayuya, and J. K. Mwangi (2015). Demand for agricultural extension services among small-scale maize farmers: Micro-level evidence from Kenya. *Journal of Agricultural Education and Extension 21*(2), 177–192.

Goecke, H., W. J. Luhan, and M. W. Roos (2013). Rational inattentiveness in a forecasting experiment. *Journal of Economic Behavior and Organization 94*(2013), 80–89.

Gollin, D. and C. Udry (2017). Heterogeneity, measurement error, and misallocation: Evidence from African agriculture. Unpublished working paper.

Handel, B. and J. Schwartzstein (2018). Frictions or mental gaps: What's behind the information we (don't) use and when do we care? *Journal of Economic Perspectives 32*(1), 155–78.

Hanna, R., S. Mullainathan, and J. Schwartzstein (2014). Learning through noticing: Theory and evidence from a field experiment. *Quarterly Journal of Economics 129*(3), 1311–1353.

Haushofer, J. and E. Fehr (2014). On the psychology of poverty. *Science 344*(6186), 862–867.

IFAD (2013). *Smallholders, food security, and the environment.* International Fund for Agricultural Development, Rome.

Jama, B. and G. Pizarro (2008). Agriculture in Africa: Strategies to improve and sustain smallholder production systems. *Annals of the New York Academy of Sciences 1136*(1), 218–232.

Jayachandran, S. (2006). Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy 114*(3), 538–575.

Jensen, R. (2000). Agricultural volatility and investments in children. *American Economic Review 90*(2), 399–404.

Kacperczyk, M., S. Van Nieuwerburgh, and L. Veldkamp (2016). A rational theory of mutual funds' attention allocation. *Econometrica 84*(2), 571–626.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry (2014). Agricultural decisions after relaxing credit and risk constraints. *Quarterly Journal of Economics 129*(2), 597–652.

Kochar, A. (1995). Explaining household vulnerability to idiosyncratic income shocks. *American Economic Review 85*(2), 159–164.

Kőszegi, B. and A. Szeidl (2013). A model of focusing in economic choice. *Quarterly Journal of Economics 128*(1), 53–104.

Luo, Y. (2008). Consumption dynamics under information processing constraints. *Review of Economic Dynamics 11*(2), 366–385.

Maćkowiak, B. and M. Wiederholt (2009). Optimal sticky prices under rational inattention. *American Economic Review 99*(3), 769–803.

Maćkowiak, B. and M. Wiederholt (2015). Business cycle dynamics under rational inattention. *Review of Economic Studies 82*(4), 1502–1532.

Mani, A., S. Mullainathan, E. Shafir, and J. Zhao (2013). Poverty impedes cognitive function. *Science 341*(6149), 976–980.

Mankiw, N. G. and R. Reis (2002). Sticky information versus sticky prices: A proposal to replace the New Keynesian Phillips curve. *Quarterly Journal of Economics 117*(4), 1295–1328.

Martin, D. (2017). Strategic pricing with rational inattention to quality. *Games and Economic Behavior 104*(2017), 131–145.

Matějka, F. and A. McKay (2015). Rational inattention to discrete choices: A new foundation for the multinomial logit model. *American Economic Review 105*(1), 272–98.

Morris, M., V. Kelly, R. Kopicki, and D. Byerlee (2007). *Fertilizer use in African agriculture: Lessons learned and good practice guidelines*. World Bank, Washington, DC.

Moser, C. M. and C. B. Barrett (2006). The complex dynamics of smallholder technology adoption: The case of SRI in Madagascar. *Agricultural Economics 35*(3), 373–388.

Munshi, K. (2004). Social learning in a heterogeneous population: Technology diffusion in the Indian Green Revolution. *Journal of Development Economics 73*(1), 185–213.

Naeher, D. (2018). Agricultural input decisions in the presence of complementarities: A rational inattention model. Unpublished working paper.

OECD/FAO (2016). *Agricultural Outlook 2016-2025*. OECD Publishing, Paris.

Rivera, W. and G. Alex (2005). *Extension reform for rural development: Case studies of international initiatives*. World Bank, Washington, DC.

Sallee, J. M. (2014). Rational inattention and energy efficiency. *Journal of Law and Economics 57*(3), 781–820.

Schultz, T. W. (1964). *Transforming Traditional Agriculture*. Yale University Press.

Sheahan, M. and C. B. Barrett (2017). Ten striking facts about agricultural input use in Sub-Saharan Africa. *Food Policy 67*(2017), 12–25.

Sims, C. A. (2003). Implications of rational inattention. *Journal of Monetary Economics 50*(3), 665–690.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica 79*(1), 159–209.

Tutino, A. (2013). Rationally inattentive consumption choices. *Review of Economic Dynamics 16*(3), 421–439.

Udry, C. (1995). Risk and saving in Northern Nigeria. *American Economic Review 85*(5), 1287–1300.

United Nations (2005). *World Public Sector Report 2005: Unlocking the Human Potential for Public Sector Performance*. United Nations, New York.

Van Nieuwerburgh, S. and L. Veldkamp (2010). Information acquisition and under-diversification. *Review of Economic Studies 77*(2), 779–805.

Wiederholt, M. (2010). Rational inattention. *The New Palgrave Dictionary of Economics (Online Edition ed.)*.

World Bank (2008). *World Development Report 2008: Agriculture for Development*. World Bank, Washington, DC.

World Bank (2015). *World Development Report 2015: Mind, society, and behavior*. World Bank, Washington, DC.

World Bank (2016). *Living Standard Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA)*. URL: www.worldbank.org/lsms-isa.

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 (analogously for 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 ($\phi_A^2\sigma_{z_A}^2 \uparrow$), as well as smaller cost of being attentive to a_A ($\mu_A \downarrow$).

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 (2016).

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. In all included survey rounds, farmers are asked to rate the quality of the received advice. 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 compare the information between countries (see Table 1), responses have been classified 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.

Farm output and productivity. The variable *Harvest* is based on farmer-reported estimates of the value of harvested crops for individual plots. In Malawi and Uganda, 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. These prices are then used to assign monetary values to farmers' harvests. This is necessary, because many farmers do not sell (all) harvested crops, and there is no data collected on the value of crops that are not sold. In Nigeria, farmers are asked directly what would have been the total value of their harvest, if everything had been sold at current market prices.

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, which we use to construct a proxy for farmers' profits. The *Profit* variable captures farmers' total value of harvest net of the estimated value of used seeds, fertilizer, and other agrochemicals (pesticides, herbicides, etc.). For these three inputs, we observe both quantities and costs of the applied inputs, including costs for purchasing, transportation to the farm, and obtaining input coupons (in Malawi). In most surveys, information on incurred costs is 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 type of input, which we then use to assign values to those inputs which are left over from the previous season, about which information is also provided in the data.

Labor and modern farm inputs. While all surveys collect data on agricultural inputs used by farmers, 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 the other inputs (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 fertilizer and agrochemicals, we also observe applied quantities. The corresponding household-level variables are obtained by summing up reported quantities across individual plots belonging to a household.

With regard to labor input, we observe the amount of labor provided by family members as well as the incurred costs for hired labor (based on farmer-specific information about average daily wages, number of hired persons, and number of days for which laborers were hired). To capture both types of labor in a single variable, we use the information on costs for hired labor to impute monetary values for provided family labor (assuming the same wages as for hired labor).

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)
Profit	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, 2016). 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 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, 2016).

Table A3: Sources of advice by 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, 2016).

Table A4: Shocks to households by 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
Agricultural shock	61.7	91.7	94.7	9.7	13.0	13.4	58.5	36.8	30.9	35.9
Drought/irregular rains	42.9	60.3	85.4	2.6	1.8	4.2	55.4	31.9	23.9	32.1
Floods/landslides	4.6	13.5	17.5	2.5	10.4	3.5	3.1	5.0	6.9	4.0
Crop pests or disease	6.5	17.6	20.0	1.3	0.6	0.6	6.0	1.7	2.7	2.3
Livestock disease	7.1	19.7	17.6	2.4	1.1	1.9	3.4	1.7	1.3	0.7
Increase in price of agricultural inputs	32.3	82.2	63.6	2.2	0.0	4.5	2.6	0.9	1.2	2.0
Fall in price of agricultural output	15.3	37.0	26.5	0.9	0.0	1.0	2.3	1.6	1.6	0.8
Non-agricultural shock	30.5	46.2	43.5	12.2	17.0	12.9	24.0	17.3	11.2	10.5
Illness or accident of household member	12.5	16.2	20.9	2.6	3.1	2.0	13.1	10.7	5.2	3.9
Death or disability of household member	4.6	8.7	17.1	3.0	4.9	3.3	3.8	3.0	1.9	3.5
Loss of employment	0.7	3.4	11.7	0.2	0.1	0.2	0.1	0.2	0.0	0.1
Reduction in non-farm income	4.4	9.7	18.2	1.5	2.5	2.6	0.9	0.1	0.2	0.1
Theft of money/valuables	5.9	9.9	17.9	1.4	1.5	3.6	8.3	3.7	1.8	2.4
Fire/earthquake/other damage	7.6	2.8	11.4	1.5	4.4	1.3	0.9	0.9	0.8	0.5
Conflict/violence	3.2	6.5	15.5	0.9	0.6	0.0	1.2	0.9	2.0	0.4
End of assistance/remittances	1.7	11.1	15.5	2.5	1.7	1.5				
Not classified										
Increase in prices for food	25.6	81.9	70.8	3.4	5.9	15.3				
Other	7.0	11.4	17.5	1.0	1.5	1.0	3.9	2.4	2.0	1.8
Observations	2,593	3,038	1,887	3,047	2,884	2,840	2,231	2,041	2,144	2,388

Notes: Numbers are percentages of households that experienced indicated shock. [a]Exact wording differs between countries. *Source:* Authors' calculation based on survey data from the LSMS-ISA database (World Bank, 2016).

C Robustness

Table A5: 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 A6: Test of model predictions: Robustness to different ways of clustering

	(1) Advice	(2) Advice	(3) Extension	(4) Extension	(5) Solicited Extension	(6) Solicited Extension
AgShock	0.087*	0.087***	0.072*	0.072***	0.061**	0.061***
	(0.096)	(0.000)	(0.083)	(0.000)	(0.038)	(0.000)
NonAgShock	0.033*	0.033***	0.030*	0.030**	0.025*	0.025**
	(0.096)	(0.007)	(0.078)	(0.020)	(0.058)	(0.025)
HH FE	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Cluster	2-way	district	2-way	district	2-way	district
Observations	20,392	20,392	20,392	20,392	19,653	19,653

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. p-values in parentheses. Clusters and associated numbers of clusters are as follows: "district" (158); "2-way": stratum (24) × wave (up to 4). 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 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 A8: Extension and farm outcomes: Robustness

	(1) log(Harv)	(2) log(Harv)	(3) log(Harv)	(4) log(Harv)	(5) log(Profit)	(6) log(Profit)	(7) log(Profit)	(8) log(Profit)
AgShock	-0.114***	-0.114**	-0.113***	-0.113**	-0.092**	-0.092	-0.102**	-0.102*
	(0.002)	(0.031)	(0.002)	(0.038)	(0.042)	(0.103)	(0.024)	(0.099)
Extension	0.083***	0.083*			0.119***	0.119**		
	(0.002)	(0.058)			(0.000)	(0.042)		
Sol. Exten.			0.098***	0.098**			0.138***	0.138**
			(0.000)	(0.019)			(0.000)	(0.010)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Sample restr.[a]	yes	yes	yes	yes	yes	yes	yes	yes
Clusters	stratum	2-way	stratum	2-way	stratum	2-way	stratum	2-way
Observations	14,230	14,230	13,648	13,648	13,747	13,747	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 A9: Extension and production choices: Robustness

	(1) Cult. Area (in ha)	(2) Cult. Area (in ha)	(3) Harvest per ha (US$)	(4) Harvest per ha (US$)	(5) log(Cost Inputs)	(6) log(Cost Inputs)	(7) log(Cost Labor)	(8) log(Cost Labor)
AgShock	-0.133	-0.139	-130.619	-132.578	0.226	0.246	-0.073	-0.062
	(0.586)	(0.586)	(0.127)	(0.128)	(0.190)	(0.167)	(0.456)	(0.540)
Extension	0.141		62.895*		0.237*		-0.101	
	(0.238)		(0.076)		(0.086)		(0.302)	
Sol. Exten.		0.060		53.639		0.270**		0.011
		(0.676)		(0.129)		(0.044)		(0.879)
HH FE	yes	yes	yes	yes	yes	yes	yes	yes
Wave FE	yes	yes	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes	yes	yes
Sample restr.^{a}	yes	yes	yes	yes				
Cluster	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way
Observations	19,122	18,415	15,351	14,722	19,391	18,680	19,092	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 A10: Extension and modern input use: Robustness

	Improved Seeds		Fertilizer				Agrochemicals			
			Any	Any	log(Qty)	log(Qty)	Any	Any	log(Qty)	log(Qty)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AgShock	-0.015	-0.017	-0.005	-0.002	-0.083	-0.058	-0.002	0.000	-0.010	0.005
	(0.510)	(0.488)	(0.681)	(0.870)	(0.473)	(0.616)	(0.810)	(0.983)	(0.860)	(0.931)
Extension	0.033		0.014		0.107		0.031		0.202	
	(0.154)		(0.143)		(0.179)		(0.151)		(0.145)	
Sol. Exten.		0.042*		0.020*		0.192*		0.031		0.203
		(0.074)		(0.062)		(0.085)		(0.203)		(0.194)
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
Cluster	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way	2-way
Observations	14,132	13,469	19,331	18,620	19,298	18,589	19,376	18,665	19,342	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.