Agricultural input decisions in the presence of complementarities: A rational inattention model

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Abstract

This paper investigates an empirical puzzle in technology adoption: the observation that farmers in Sub-Saharan Africa who have successfully adopted modern agricultural inputs on their farm tend to spread synergistic inputs across plots rather than combining them. Existing theories are unable to account for this behavior, because they focus on explaining adoption decisions of individual inputs and abstract from the complexity of these decisions in the presence of complementarities. This paper proposes a novel explanation that is based on a rational inattention channel. In the model, combining modern inputs offers potential synergy effects, but cultivation practices have to be adapted to specific field and seasonal conditions in order to achieve optimal outcomes. By devoting attention to their plots, farmers can reduce uncertainty about optimal practices and thereby increase the expected return of joint input use. I show that taking into account a limited attentional capacity can explain why farmers may rationally decide not to combine complementary inputs on the same plots or abstain from adopting profitable inputs altogether. The identified mechanism is in line with evidence on the limits of human cognition and generates testable predictions that coincide well with empirical patterns in agricultural input use.

Keywords: input complementarity, rational inattention, agriculture
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"...households that are using multiple modern inputs tend to spread them across plots rather than concentrating them on single plots. This behavior has gone largely unstudied to date and raises important questions about prospective untapped productivity gains from coordinated modern inputs use."

- Sheahan and Barrett (2017)

1 Introduction

Increasing agricultural productivity remains one of the key challenges for many African countries in achieving food security and fostering sustainable economic growth and development (Gollin, 2010; Christiaensen et al., 2011; OECD/FAO, 2016). It is commonly argued that a crucial factor to accomplish this consists in the diffusion and proper adoption of modern agricultural input technologies, such as improved seed varieties, inorganic fertilizer, and irrigation systems.[1] An important feature of these inputs is that they tend to be most productive when applied in combination with each other, as coordinated use can create agronomic synergies.[2] Many studies thus highlight the importance of joint adoption of modern inputs in order to raise agricultural productivity (Morris et al., 2007; Sheahan et al., 2013; Nyangena and Juma, 2014).

Despite the strong expectation that farmers will use modern inputs in combination with each other, recently collected data from Sub-Saharan Africa shows that there is a surprisingly low correlation between the use of commonly paired inputs at the plot level. Pooling information from several nationally representative datasets, I find that less than 20 percent of plots are cultivated using more than one modern input (including fertilizer, improved seeds, agrochemicals, and irrigation), and less than 3 percent of plots receive combinations of three or more different inputs. Furthermore, even among those households that are already using two or more of these inputs on their farm, more than 40 percent of cultivated plots receive none or only one of the considered inputs, and only around 7 percent of plots are cultivated with combinations of at least three inputs. This implies that most farmers seem to apply complementary inputs rather as substitutes instead of combining them on the same plots. As recently pointed out by Sheahan and Barrett

[1] These inputs are usually seen as the main drivers behind the dramatic increases in agricultural productivity during the Green Revolution in Asia and Latin America, and many studies argue that African farmers could achieve similar high productivity gains by adopting these inputs in appropriate ways (Evenson and Gollin, 2003; Morris et al., 2007; Jama and Pizarro, 2008; FAO, 2014).

[2] For example, fertilizer tends to yield higher returns on irrigated plots, as it requires a certain soil moisture to effectively enhance plant growth (Duflo and Pande, 2007; Morris et al., 2007). Since fertilizer also facilitates the growth of undesired weeds, it may optimally be combined with other agrochemicals such as herbicides (Beaman et al., 2013; Sheahan and Barrett, 2017). In addition, many new seed varieties are designed to be paired with fertilizer and pesticide, and some estimates suggest complementarities of up to 70 percent between these inputs (Ellis, 1992; Nyangena and Juma, 2014; Abay et al., 2016).

(2017), this behavior has remained largely unstudied until now. I believe there are at least two reasons for this. First, the vast majority of studies in the context of agricultural technology adoption focus on adoption decisions for individual input technologies. This often allows authors to abstract from the complexity of adoption decisions in the presence of complementarity between different inputs.[3] Second, many datasets on agriculture in the development context are collected at the household level. However, since agronomic synergies only arise when inputs are combined on the same fields, it requires information at the plot level to study relevant usage decisions of complementarity inputs.

In the economic literature, various theories have been proposed to explain suboptimal adoption of modern agricultural inputs. This includes explanations based on imperfect markets for land, credit, and insurance (Moser and Barrett, 2006; Dercon and Christiaensen, 2011; Karlan et al., 2014), individual and social learning (Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010), low profitability due to transaction costs and other factors (Suri, 2011; Bold et al., 2017), as well as behavioral channels such as procrastination (Duflo et al., 2011). It is important to note that these studies focus almost exclusively on explaining adoption decisions for individual input technologies. In addition, most of the existing theories in this context are based on factors at the household level. While such factors may determine whether farmers are generally able and willing to adopt certain inputs on their farms, they are typically unsuited to account for within-household variation in input use. There is thus a need for alternative channels to explain the empirical discrepancy between sets of inputs used on farm and the apparent misallocation of complementary inputs at the plot level.

This paper addresses this gap by proposing a novel framework to study agricultural input decisions in the presence of complementarities. In line with a growing body of literature that highlights the role of limitations in human cognition for economic decision-making (DellaVigna, 2009; Maćkowiak et al., 2009; Beaman et al., 2014; Bartoš et al., 2016), I investigate optimal agricultural input choices under the assumption of rationally inattentive farmers. In doing so, I build on existing work in the rational inattention literature (Sims, 2003; Maćkowiak and Wiederholt, 2009; Matêjka and McKay, 2015) and particularly the model of technology adoption under rational inattention developed in Naeher (2017).[4] In the model, combining modern inputs together on the same plots offers potential synergy effects, but cultivation practices have to be adapted to the specific conditions on each plot in order to achieve optimal outcomes. By devoting attention to their plots, farmers can reduce uncertainty about optimal practices and thereby increase the expected return of

[3] As pointed out by other authors, considering complementarities between inputs can lead to methodological challenges for the identification strategies used in many of these studies (Foster and Rosenzweig, 2010; Beaman et al., 2013; Abay et al., 2016).

[4] While standard models in economics implicitly assume that processing information is instantaneous and costless, the rational inattention literature uses an entropy-based limited-capacity channel to capture the mental cost associated with being attentive.

joint input use. The solution of the model shows that optimal adoption behavior depends not only on economic factors that determine the profitability of modern input use (such as prices, returns, and transaction costs), but also on farmers' (mental) opportunity cost of attention. In particular, the model suggests that if attention is very scarce (i.e., the mental opportunity cost of attention is sufficiently large), non-adoption of profitable and readily available modern inputs can be a rational decision. The reason for this is that without enough attention, the farmer is unable to observe the current state of his plots and planted crops, and is therefore too much at risk of selecting inadequate input practices. If more attention is available, input combinations that require more complex usage choices, but also offer potentially larger returns, are optimal.

The identified mechanism generates a number of testable predictions that correspond well with empirical patterns in agricultural input use commonly observed in Sub-Saharan Africa. For example, the model can explain why farmers use modern inputs in suboptimal ways and only imperfectly adapt their cultivation practices to changing conditions in the environment (e.g., prices, weather, and occurrence of pests and diseases). At the plot level, the model can account for the observation that farmers spread complementary inputs across plots or jump in and out of joint input use (switching behavior). The model also generates predictions about how farmers will respond to information and attention-related interventions (such as reminders and agricultural advice in pre-processed form), which correspond well with the findings of recent field experiments (Cole and Fernando, 2013; Casaburi et al., 2014; Hanna et al., 2014). In addition, the model suggests that constraints on attention can cause farmers to abstain completely from adopting otherwise profitable input technologies. This offers an alternative mechanism to explain persistently low adoption rates of modern inputs which can complement the insights of existing theories in this context and has interesting implications for extension programs and policies aimed at increasing agricultural productivity through the adoption of more efficient input practices.

The remainder of the paper is organized as follows. Section 2 presents the model and derives the optimal input choice behavior for rationally inattentive farmers. Section 3 tests the predictions of the model based on empirical evidence on agricultural input use in Sub-Saharan Africa. Section 4 discusses the relationship of the model to alternative theories in this context. Section 5 concludes.

2 A rational inattention model of joint input use

This section develops a new framework to study agricultural input decisions in the presence of complementarity. The approach relies on three main assumptions. First, the returns to modern agricultural inputs depend on accompanying usage choices that farmers have to make, e.g. about timing, composition, and quantity of applied inputs. Second, optimal practices are sensitive to changes in the underlying conditions, such as prices, weather, or presence of certain diseases. Third, farmers do not perfectly observe the current conditions and have to exert costly mental effort to derive the associated optimal practices. Based on these assumptions, I demonstrate how the behavior of a rationally inattentive agent can be used to explain key patterns of empirical input use in African agriculture, including some of the observations which existing models are unable to account for.[5]

2.1 Actions, states, and returns

I study the decision problem of a farmer who owns two plots and has access to two complementary modern input technologies, denoted as S and F (e.g., improved seed variety and fertilizer). For each plot $j \in \{1, 2\}$, the farmer chooses among $k \in \mathcal{K}$ actions, which are listed in the first column of Table 1. In particular, the farmer can choose not to adopt any modern input, to apply a single input, or to combine both inputs together. Whenever an input is used on a plot, it can be applied in two different ways (e.g., low and high quantity, or early and late timing). Let these two options be denoted as *low* (l) and *high* (h), respectively. In addition, let the outside option of not using a specific input be denoted as 0. In this stylized framework, the farmer thus selects among nine possible actions for each plot: non-adoption of any modern input, four possible ways of using a single input on a plot, as well as four possible ways of using two complementary inputs jointly.[6]

The outcome of an action on plot j depends on the state of the world on plot j. Let $v_{j,k}$ denote the return for action k on plot j, and let $\mathbf{v}_j$ denote the (9×1) vector containing the returns for all possible actions on plot j. The return for a given action depends on the plot state z_j. One can think of z_j as capturing the current conditions on each plot (e.g., temperature, soil moisture, and presence of pests and diseases) as well as other fundamentals such prices for inputs and outputs. There are four possible state realizations, which are denoted as $z_j \in \{(l, l), (l, h), (h, l), (h, h)\}$.[7] If the state (l, l) realizes, then $\mathbf{v}_j$ equals the corresponding column in Table 1. Non-adoption of any modern input yields a safe return of R, normalized to zero. Adequate application of a single input yields a return equal to a. Therefore, the returns of the actions $(S_l, 0)$ and $(0, F_l)$ in the (l, l) state equal a. Inadequate application of an input yields a return equal to $-b$. Hence,

[5] Formally, the model builds on existing work in the rational inattention literature (Sims, 2003; Maćkowiak and Wiederholt, 2009; Matějka and McKay, 2015) and particularly the model of technology adoption under rational inattention developed in Naeher (2017).

[6] In the following, I use the terms 'action', 'input choice', and 'cultivation practice' interchangeably.

[7] I use the notation (l, h) to indicate that in this state the optimal way of applying the first input is *low* and the optimal way of applying the second input is *high*.

Table 1: Return $v_{j,k}$ given plot state z_j and action k

	$k \in \mathcal{K}$	z_j				$E[v_{j,k} \mid \kappa_j = 0]$*
		(l,l)	(l,h)	(h,l)	(h,h)	
Non-adoption	$(0,0)$	0	0	0	0	$R = 0$
Single input	$(S_l, 0)$	a	a	$-b$	$-b$	$\frac{1}{2}(a-b)$
	$(S_h, 0)$	$-b$	$-b$	a	a	
	$(0, F_l)$	a	$-b$	a	$-b$	
	$(0, F_h)$	$-b$	a	$-b$	a	
Joint inputs	(S_l, F_l)	$a(1+c)$	$a-b$	$a-b$	$-2b$	$\frac{1}{4}a(3+c)-b$
	(S_l, F_h)	$a-b$	$a(1+c)$	$-2b$	$a-b$	
	(S_h, F_l)	$a-b$	$-2b$	$a(1+c)$	$a-b$	
	(S_h, F_h)	$-2b$	$a-b$	$a-b$	$a(1+c)$	

Note: *Expected return when no attention is devoted to the plot (i.e., simple expected value). Each state of the fundamental z_j is realized with equal probability 1/4.

the returns of the actions $(S_h, 0)$ and $(0, F_h)$ in the (l,l) state equal $-b$. Furthermore, adequate application of both inputs jointly creates synergy effects. For this reason, the return of the action (S_l, F_l) in the (l,l) state equals $a(1+c)$ with $c > 0$. If one of the two inputs is applied inadequately, the synergy is lost and the joint return equals the sum of the individual returns.

In order to be able to capture the full spectrum of farmers' input choices, I focus on parameter value ranges that ensure that all actions represent relevant alternatives for the farmer. In the stylized framework considered here, this requires that $0 < a < b$ and $c < 2\frac{b}{a} - 1$ (see Appendix A).[8] In particular, this implies that using inputs without devoting any attention to the plot is dominated by the outside option (i.e., the expected values shown in the last column of Table 1 are smaller than the secure return under non-adoption). For ease of exposition, I furthermore focus on the case where each state is realized with equal probability and states are independent across the two plots.

It should be noted that the distribution of returns specified in Table 1 captures two main ideas, which can be summarized by the following two assumptions.

Assumption 1. *Farmers face uncertainty about how to apply modern agricultural inputs, because optimal practices depend on current conditions which are not perfectly observed.*

Assumption 2. *Adoption of modern inputs is profitable, provided they are applied in adequate ways. Suboptimal practices are associated with lower profitability and, for some states of the world, lead to smaller net returns than those under non-adoption.*

[8] Notice that these assumptions could be relaxed by considering more than two possible options for each input. For example, if the farmer had to choose the correct action for each input among N symmetric alternatives, the expected value of using a single input without attention would be $E[v_{j,k}] = \frac{1}{N}[a - b(N-1)]$, such that the restriction $a < b$ could be relaxed to $a < (N-1)b$.

Assumption 1 corresponds to the idea that the profitability of modern inputs depends on accompanying choices farmers make when applying these inputs (e.g., related to timing, quantity, and different ways of combining inputs with each other). This introduces additional uncertainty into the farmer's decision problem, because cultivation practices have to be chosen in conformity with the realized states of each plot to generate optimal outcomes.[9] It is important to note that Assumption 1 is in line with a large number of studies that argue that the returns to modern agricultural inputs depend crucially on adequate cultivation practices and the need to adapt these practices to idiosyncratic conditions and shocks in the environment (Duflo et al., 2008; Marenya and Barrett, 2009; Conley and Udry, 2010; Sheahan et al., 2013; Gollin and Udry, 2017).[10] For example, Morris et al. (2007) state that the profitability of fertilizer use depends on tailoring the dosage, composition, and timing of application to specific field and seasonal conditions. In a similar way, Cole and Fernando (2013) state that because of seasonal variation in the types and resistance of pests, constant adjustment in the type and quantity of pesticides used are required for effective pest control.

Assumption 2 captures the idea that farmers can achieve higher profits with adequate use of modern inputs than without these inputs. Inadequate practices, on the other hand, are associated with lower profitability and can potentially lead to smaller net returns than those under non-adoption (e.g., this may be the case if the additional yield from fertilizer use is not enough to cover the expenses for fertilizer which is applied in suboptimal quantity or timing).[11] Assumption 2 is supported by empirical evidence on the returns to modern inputs in African agriculture. For example, in a series of field experiments conducted in Kenya, Duflo et al. (2008, 2011) test the profitability of inorganic fertilizer for a randomized group of farmers under real conditions (i.e., not on test farms). Their results show that (i) farmers face considerable uncertainty about profitable quantities of fertilizer use, (ii) appropriate quantities of fertilizer can raise farmers' annual income by up to 70 percent, and (iii) suboptimal quantities are associated with negative net returns.[12]

These findings conform with the results of other studies in this context (including for other modern inputs such as improved seed varieties), and with the view held by many agricultural experts (Jama and Pizarro, 2008; Marenya and Barrett, 2009; World Bank,

[9]Notice that this differs from the assumptions typically made in learning models of technology adoption, where agents update beliefs about fixed target values (see discussion in Section 4).

[10]This includes the growing literature on precision agriculture, which argues that even conditions at the micro level (i.e., within individual plots) can have significant effects on the profitability of different input practices (e.g., Koch et al., 2004; Lambert et al., 2006).

[11]Note that the existence of a riskless outside option is a common assumption in models of agricultural input choices (Munshi, 2004; Bandiera and Rasul, 2006; Foster and Rosenzweig, 2010).

[12]Duflo et al. (2008) summaries their findings with the words, "*...while fertilizer can be very profitable when used correctly, one reason why farmers may not use fertilizer and hybrid seeds is that the official recommendations are not adapted to many farmers in the region. This also suggests that fertilizer is not necessarily easy to use correctly, which implies that it may not be profitable for many farmers who do not use the right quantity.*"

2007; FAO, 2014). In a similar way, it is often argued that joint use of modern inputs can lead to higher returns than single input use, provided that inputs are paired in adequate ways (see references listed in footnote 2).

2.2 Information processing

While the farmer is assumed to know the structure of returns given in Table 1, he does not directly observe the realization of states z_j, $j \in \{1, 2\}$. To reduce uncertainty about the realization of z_j and associated values $\mathbf{v}_j$, the farmer can process relevant information.[13] Let the prior belief which the farmer may have over the realized states be given by the distribution $G(\mathbf{z})$, where $\mathbf{z} = (z_1, z_2)$. Processing information about the state of plot j can be modeled as receiving a signal s_j about the realization of z_j. The farmer's actions are based on the resulting posterior beliefs, denoted as $\Gamma(\mathbf{z} \mid \mathbf{s})$.

In line with a growing body of evidence on the limits of human cognition, information processing requires attentional effort and the farmer face a limited amount of endowed attention (Gabaix et al., 2006; DellaVigna, 2009; Goecke et al., 2013; Bartoš et al., 2016). Let κ_j denote the amount of attention that is allocated to reducing uncertainty about the state of plot j and let the total amount of endowed attention be given by $\overline{\kappa} > 0$. Limited attention is modeled as a constraint on uncertainty reduction. Following the literature on rational inattention, uncertainty is quantified by entropy, a measure of the unpredictability of a random variable's realization (Sims, 2003; Maćkowiak and Wiederholt, 2009; Matêjka and McKay, 2015). This is formally captured by the constraint

$$H(G(z_j)) - E_s \left[H(\Gamma(z_j \mid s_j)\right] \leq \kappa_j, \quad j \in \{1, 2\} \tag{1}$$

where $H(G(z_j))$ denotes the prior entropy associated with the choice problem for plot j, and $E_s \left[H(\Gamma(z_j \mid s_j)\right]$ is the expected posterior entropy after the farmer has processed information. In particular, condition (1) states that the more attention is devoted to plot j, the larger is the expected reduction in uncertainty (measured in entropy) about the plot's realized state. In the case of a discrete choice problem considered here, entropy is defined as follows.

Definition 1 (Prior and posterior entropy). *For discrete states z_j, the entropy of the prior belief $G(z_j)$ is given by*

$$H(G(z_j)) = -\sum_{z_j} \Pr(z_j) \log_2 \Pr(z_j), \tag{2}$$

[13] Note that without the possibility to process information, farmers' decision problem would correspond to a simple portfolio selection problem (i.e. where farmers have to choose an optimal mixture of input combinations that differ in respect to their riskiness and expected returns). In the framework considered here, however, farmers have control over the respective levels of risk, as they are able to reduce uncertainty by being attentive to the conditions on their plots.

where $\Pr(z_j)$ *is the probability of state* z_j*. The posterior entropy given the signal* s_j *is given by*

$$H(\Gamma(z_j \mid s_j) = -\sum_{z_j} \Pr(z_j \mid s_j) \log_2 \Pr(z_j \mid s_j). \tag{3}$$

For the prior and posterior beliefs to be consistent, it must hold that $G(\mathbf{z}) = \int_{\mathbf{s}} \Gamma(d\mathbf{s}, \mathbf{z})$. Other than that, there are no further restrictions imposed on the properties of $\mathbf{s}$. In choosing the signal, the farmer is thus free to select among all possible joint distributions of signals and states, $\Gamma(\mathbf{s}, \mathbf{z}) \in \Delta$.[14] Obviously, the most informative set of signals a farmer could choose is to select a different signal s_j for each possible state z_j and perfectly distinguish between all states. However, choosing such a set of signals would be very costly. This is illustrated in Figure 1, which shows the relationship between the degree of a signal's informativeness and its attentional cost for a special case of single input use. Suppose the farmer intents to use S as a single input on plot j. In this case, the farmer only cares about the first component of z_j, i.e. whether z_j equals $(l, \cdot)$ or $(h, \cdot)$. One possible strategy of the farmer could thus be to choose a binary signal $s \in \{0, 1\}$ with the following structure:

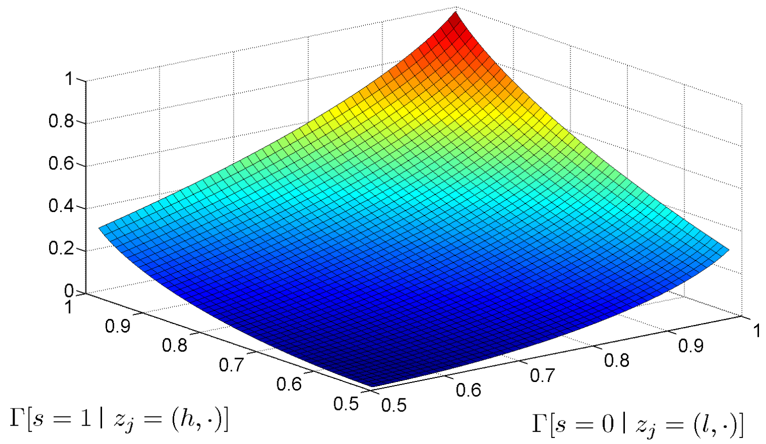
$$\begin{aligned}
\Gamma\left[s = 0 \mid z_j = (l, \cdot)\right] &= p \\
\Gamma\left[s = 1 \mid z_j = (l, \cdot)\right] &= (1 - p) \\
\Gamma\left[s = 1 \mid z_j = (h, \cdot)\right] &= q \\
\Gamma\left[s = 0 \mid z_j = (h, \cdot)\right] &= (1 - q)
\end{aligned}$$

This mean that the farmer would receive a signal of $s = 0$ with probability p (and a signal $s = 1$ with probability $1 - p$) whenever the realized state on plot j is $(l, \cdot)$. In addition, the farmer would receive a signal of $s = 1$ with probability q (and a signal of $s = 0$ with probability $1 - q$) whenever the realized state is $(h, \cdot)$. For this particular structure, choosing $(p, q) = (1, 1)$ would allow the farmer to perfectly distinguish between states $(l, \cdot)$ and $(h, \cdot)$.[15] Therefore, at this point the highest attentional cost depicted in Figure 1 is attained. In contrast, setting $(p, q) = (0.5, 0.5)$ would not provide any additional value for the farmer, since he would always receive signals of $s = 0$ and $s = 1$ with equal probability, independent of the realized state. The associated cost at this point is therefore zero. Any signal structure between these two extremes allows the farmer to partially reduce uncertainty about the realized state, leading to the corresponding cost shown in Figure 1.

[14] Notice that this endogenizes the structure of information processing in the model. This differs from other limited attention models in economics which let the decision maker choose only the precision of the signal, but not the distribution from which the signal is drawn (e.g., DellaVigna, 2009; Hanna et al., 2014; Karlan et al., 2016).

[15] Alternatively, this could also be achieve for $(p, q) = (0, 0)$.

Figure 1: Attentional cost of information processing



It should be noted that modeling farmers as rationally inattentive decision makers relies on the following assumption.

Assumption 3. *Farmers have access to information which is helpful in deriving optimal ways of applying agricultural inputs. In attending to this information, farmers face a limited information processing capacity and decide rationally how to allocate their attention.*

Regarding the first part of Assumption 3, it may be helpful to distinguish between two different types of relevant information: internal information, which is generated by the production process itself, as well as information from external sources (see Hanna et al., 2014). The former includes information about the prevailing conditions on each plot, such as plant growing stage, soil quality, and signs of erosion, aridity, or diseases. Attending to this information is crucial, as optimal input practices are significantly affected by the conditions on each plot (see discussion for Assumption 1). In addition, farmers may have access to external sources of information which are helpful in choosing better practices (e.g., other farmers, different types of media, or agricultural extension services).[16]
The second part of Assumption 3 captures the idea that farmers have to exert costly mental effort to absorb and incorporate information into their decision-making, even if this information is directly available to them. In processing information, farmers are assumed to allocate their attention rationally. Although this has been criticized as a strong assumption in similar contexts (e.g. Schwartzstein, 2014), there exists a growing body of empirical work which supports this feature (Gabaix et al., 2006; Maćkowiak et al., 2009; Caplin and Dean, 2013; Goecke et al., 2013; Bartoš et al., 2016).[17]

[16]While in principle getting access to such information may be costly, in many instances these costs may be negligible (e.g., talking to a neighbor or asking a shopkeeper).

[17]An alternative approach to rational inattention are stimulus-driven models of attention allocation which emphasize the importance of salience over the true value carried by information (Bordalo et al., 2013; Kőszegi and Szeidl, 2013). In these models, attention allocation is exogenous to the decision maker and determined by external signals rather than by optimizing behavior.

2.3 Decision problem

The timing of the model is as follows. First, the farmer chooses the allocation of attention. This includes both the decision of how much attention to devote to each plot and the structure of the signal. For example, the farmer may choose to use all of his attention to discriminate between all possible states on plot 1, while paying no attention to the state of plot 2. Second, the state of nature realizes (e.g., the realized state on plot 1 is (l, l) and the realized state on plot 2 is (h, h)). Third, the farmer receives a signal about the state of the two plots (e.g., the signal might say that the state on plot 1 is (l, l) and the state on plot 2 is (h, l)). Recall that the signal is more likely to be correct the more attention the farmer devotes to this plot. Fourth, the farmer takes an action for each plot based on his posterior beliefs. Fifth, the farmer receives the payoff on each plot, which is determined by the combination of state and action, as described by Table 1.

Formally, the decision problem of the farmer is given as follows.

$$\max_{\{\Pr(s_j, z_j)\}} \quad \sum_{j=1}^{2} \sum_{z_j} \sum_{s_j} v_{j,k^*} \; \Pr(s_j \mid z_j) \; \Pr(z_j) \tag{4}$$

$$\text{s.t.} \qquad k^* = \arg\max_{k \in \mathcal{K}} E\left[v_{j,k} \mid s_j\right] \tag{4.1}$$

$$H(G(z_j)) - E_s\left[H(\Gamma(z_j \mid s_j)\right] \leq \kappa_j \tag{4.2}$$

$$\sum_{j=1}^{2} \mu_j \kappa_j \leq \overline{\kappa} \tag{4.3}$$

The first condition (4.1) states that the farmer chooses the action with the highest expected payoff given his posterior beliefs.[18] This corresponds to a standard choice problem under uncertainty. The second condition (4.2) states that the reduction in uncertainty about optimal actions (measured by entropy) is bounded by the amount of attention devoted to each plot. The third condition (4.3) is the budget constraint for the scarce resource attention. Notice that the parameter μ_j may differ across plots, because it may be more demanding for the farmer to process information for one plot than for another (e.g. the farmer may be more familiar with the soil type of one plot).[19]

The objective of the farmer is defined by expression (4). The term in the sum is the

[18] In some related models, this is referred to as the second stage problem, while choosing the allocation of attention is called the first stage problem (Matějka and McKay, 2015; Acharya and Wee, 2016).

[19] An alternative approach would be to model unit costs of paying attention. This would lead to an individual consideration of the optimal amount of attention paid to each plot, which would be independent of the choices for other plots. In explaining heterogeneity across plots, such an approach would thus have to rely on different plot parameter values. In contrast, the approach taken here is able to generate different optimal actions even for the case where all plots are identical.

expected payoff on plot j for the chosen signal s_j and realized state z_j. For each realized state, the expected payoff equals the product of the probability of the state, $\Pr(z_j)$, the conditional probability of the signal given the realized state, $\Pr(s_j \mid z_j)$, and the expected value of action k^* which is chosen under the obtained signal as specified in condition (4.1). The farmer chooses the structure of the signal, given by the full set of joint probabilities $\Pr(s_j, z_j)$ for each plot. In doing so, the farmer seeks to achieve higher probabilities of selecting actions that yield larger returns given the realized state. Overall, the farmer allocates his attention so as to maximize the sum of expected payoffs over the two plots, subject to the given constraints.[20] This concludes the description of the model. The next section presents the solution and discusses the main mechanism underlying the farmer's optimal behavior.

2.4 Solution of the model

The solution to the farmer's optimization problem is formally derived in Appendix A. In particular, the solution shows that the optimal action of the farmer depends on the scarcity of attention, which is captured by the opportunity cost of attention λ.[21] For plausible restrictions on the parameter values (see Appendix A), the optimal input choice behavior can be summarized as follows.

Proposition 1. *If attention is very scarce (i.e., λ is sufficiently large), the farmer optimally chooses not to adopt any modern input. As λ decreases, input combinations that require more attention, but also offer potentially larger returns, become optimal. The exact order in which actions become optimal is sensitive to the parameter values. If parameters are such that all actions represent relevant alternatives, the optimal behavior of the farmer is characterized by the following order: as attention becomes less scarce, it first becomes optimal to apply a single modern input on one plot, then on two plots, and eventually to combine both inputs on one plot and then on two plots.*

Proof. See Appendix A. □

Notice that Proposition 1 implies that choosing different combinations of inputs across plots can be an equilibrium outcome, even if plots are homogeneous. For example, it may be optimal for the farmer to combine both inputs on the first plot, but use only a

[20] Notice that the optimization problem specified by (4) - (4.3) is equivalent to a decision problem where the farmer decides first whether to adopt inputs S and F on his plots, and then selects the allocation of attention and corresponding actions.

[21] As shown in the appendix, λ corresponds to the Lagrange multiplier of restriction (4.3). For fixed parameter values (a, b, c, R, μ_1, μ_2), the size of λ follows directly from the amount of endowed attention $\overline{\kappa}$. The relation between $\overline{\kappa}$ and λ is inverse, such that λ can be interpreted as a measure of scarcity of attention in the agent's decision problem.

single input on the second plot. This is the case, if the available amount of attention is insufficient to make combining inputs on both plots profitable in expectation, given the farmer's current opportunity cost of attention.

To understand the mechanism that leads to the results in Proposition 1, it is helpful to consider the farmer's optimal allocation of attention. As the farmer can choose among all possible joint distributions of signals and states, $\Gamma(\mathbf{s}, \mathbf{z}) \in \Delta$, solving for the optimal signal structure is in general very difficult. I therefore follow the approach suggested by Matêjka and McKay (2015) and derive the farmer's optimal allocation of attention as the solution to a reformulated problem which uses state-contingent choice probabilities rather than signals. As shown by the authors, in the case of a rationally inattentive decision maker facing a discrete choice problem, every signal structure (along with a prior belief) induces a joint distribution between states and selected actions.[22] Let

$$\mathcal{P}_{j,k}(\mathrm{v}) = \Pr(k \mid \mathbf{v}_j) \tag{4}$$

denote the induced probability of selecting action k on plot j conditional on realized values $\mathbf{v}_j$ (i.e., after receiving the signal). Furthermore, let

$$\mathcal{P}^0_{j,k} = \int_V \mathcal{P}_{j,k}(\mathrm{v}) G(dV) \tag{5}$$

denote the *ex-ante* probability of selecting action k on plot j (before any information is processed). The solution to the farmer's decision problem can be derived as the solution to the reformulated optimization problem described in Appendix A. In the transformed problem, the farmer's behavior is fully characterized by the choice probabilities $\{\mathcal{P}_{j,k}(\mathrm{v})\}_{k\in\mathcal{K}}$ for each plot. The farmer directly sets these probabilities, such that it is not necessary to explicitly model signals.

The solution to the transformed problem is the set of probabilities $\{\mathcal{P}_{j,k}(\mathrm{v})\}_{k\in\mathcal{K}}$ for each plot which maximizes the sum of expected payoffs from the two plots subject to the given constraints. The following provides the solution to the farmer's decision problem based on these choice probabilities. To make the discussion more traceable, I first consider each of the three different types of actions on a plot separately, before discussing the mechanism underlying the farmer's overall input choice behavior across two plots.

Case 1: Non-adoption. If the farmer chooses not to adopt any modern input on plot j, he selects the outside option, $k = (0, 0)$, by setting $\mathcal{P}_{j,(0,0)}(\mathrm{v})$ equal to one for all states, and the probabilities of all other actions equal to zero. In this case, no information about the plot is processed and the fixed return $R = 0$ is realized with certainty.

[22] Some authors refer to this distribution as "information strategy".

Case 2: Single input use. Recall that in case a single modern input is used on a plot there are two possible ways of applying the input, given by $k \in \{(S_l, 0), (S_h, 0)\}$ or $k \in \{(0, F_l), (0, F_h)\}$, depending on which input is chosen (inputs are assumed to be homogeneous). After paying attention to the realized plot state, the farmer seeks to select the input practice which best conforms to the fundamental state of the plot. The following results hold for single input use.

Proposition 2. *The optimal behavior of a rationally inattentive farmer who adopts a single modern input (S) on plot j is characterized by the choice probabilities*

$$\left(\mathcal{P}^*_{j,(S_l,0)}(\mathrm{v}), \mathcal{P}^*_{j,(S_h,0)}(\mathrm{v})\right) = \begin{cases} \left(\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}}, \frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}}\right) & \text{if } z_j \in \{(l,l),(l,h)\} \\ \left(\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}}, \frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}}\right) & \text{if } z_j \in \{(h,l),(h,h)\} \end{cases}$$

$$\left(\mathcal{P}^{0,*}_{j,(S_l,0)}, \mathcal{P}^{0,*}_{j,(S_h,0)}\right) = \left(\frac{1}{2}, \frac{1}{2}\right),$$

where λ denotes the farmer's opportunity cost of attention (if the farmer uses F as a single input, the corresponding probabilities follow analogously). The optimal amount of attention allocated to a plot with single input use and the associated expected return are given as

$$\kappa^*_j(\lambda) = 1 + \frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}} + 2^{\frac{-b}{\lambda\mu_j}}} \log_2\left(\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}} + 2^{\frac{-b}{\lambda\mu_j}}}\right) + \frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}} + 2^{\frac{a}{\lambda\mu_j}}} \log_2\left(\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}} + 2^{\frac{a}{\lambda\mu_j}}}\right)$$

$$E[V_j(\kappa^*_j)] = \frac{a\,2^{\frac{a}{\lambda\mu_j}} - b\,2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}} + 2^{\frac{-b}{\lambda\mu_j}}}$$

Proof. See Appendix A. □

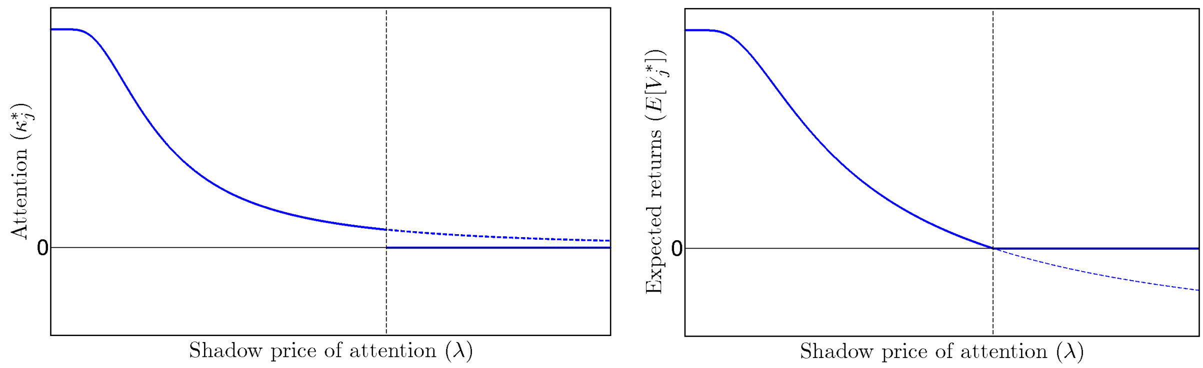
Several important implications follow from Proposition 2. First, the farmer will use adopted inputs in varying ways, seeking to adapt his practices to the current conditions (i.e., realized states). In doing so, all options that may potentially be optimal feature a positive ex-ante probability of being selected.[23]

Second, as long as the farmer is constraint by imperfect attention (i.e., $\lambda > 0$), he will occasionally select inadequate ways of using the input. The probability of making these mistakes increases, the larger the scarcity of attention.[24] It is important to note that even

[23] In the symmetric case considered here, the ex-ante probability of the two ways of using a single input is the same. This is intuitive, as both options are initially equally likely to be optimal.

[24] To see this, one should notice that the probability of selecting the wrong option according to the realized state is given by the term $2^{\frac{-b}{\lambda\mu_j}}/(2^{\frac{a}{\lambda\mu_j}} + 2^{\frac{-b}{\lambda\mu_j}})$, which depends positively on λ.

Figure 2: Optimal attention and expected returns for single input use



Note: Simulations based on varying $\overline{\kappa}$ for fixed parameter values $(a, b, R, \mu) = (1, 2, 0, 1)$.

if this causes the farmer to incur negative returns to modern input use in some periods, the use of these inputs will still represent optimal behavior (as long as the expected returns exceed those under non-adoption).

Third, if the farmer uses a modern input on a plot, he will also allocate a significant amount of attention to the plot. This follows from the fact that without sufficient attention, the farmer is unable to reduce the risk of selecting inadequate practices, and would therefore rather prefer non-adoption.

Figure 2 provides a graphical illustration for the solution of $\kappa_j^*(\lambda)$ and $E[V_j(\kappa_j^*)]$ for single input use. As shown in the first graph, as long as the input is used the optimal amount of attention is strictly positive (left to the vertical reference line). When the shadow price of attention is too large to make using the input profitable, the farmer chooses the outside option and allocates no attention to the plot (right to the reference line). The discontinuity at the cutoff appears, because adopting the technology under very small amounts of attention leads to negative expected returns, which are dominated by the outside option (as shown in the second graph). This is due to the fact that without enough attention, the farmer is too much at risk of selecting inadequate input practices.

Case 3: Joint input use. In case the farmer uses both modern inputs together on plot j, the four possible ways of combining inputs with each other are given by $k \in \{(S_l, F_l), (S_l, F_h), (S_h, F_l), (S_h, F_h)\}$. The farmer seeks to select the combination that conforms best to the fundamental state and allows him to take advantage of the complementarity between the two inputs. The following results hold for joint input use.

Proposition 3. *The optimal behavior of a rationally inattentive farmer who uses both modern inputs together on plot j is characterized by the choice probabilities*

$$\left(\mathcal{P}^*_{j,(S_l,F_l)}(\mathrm{v}),\mathcal{P}^*_{j,(S_l,F_h)}(\mathrm{v}),\mathcal{P}^*_{j,(S_h,F_l)}(\mathrm{v}),\mathcal{P}^*_{j,(S_h,F_h)}(\mathrm{v})\right)=\begin{cases}\left(\frac{\Psi^+}{\Theta},\frac{\Psi}{\Theta},\frac{\Psi}{\Theta},\frac{\Psi^-}{\Theta}\right) & \text{if } z_j=(l,l)\\ \left(\frac{\Psi}{\Theta},\frac{\Psi^+}{\Theta},\frac{\Psi^-}{\Theta},\frac{\Psi}{\Theta}\right) & \text{if } z_j=(l,h)\\ \left(\frac{\Psi}{\Theta},\frac{\Psi^-}{\Theta},\frac{\Psi^+}{\Theta},\frac{\Psi}{\Theta}\right) & \text{if } z_j=(h,l)\\ \left(\frac{\Psi^-}{\Theta},\frac{\Psi}{\Theta},\frac{\Psi}{\Theta},\frac{\Psi^+}{\Theta}\right) & \text{if } z_j=(h,h)\end{cases}$$

$$\left(\mathcal{P}^{0,*}_{j,(S_l,F_l)},\mathcal{P}^{0,*}_{j,(S_l,F_h)},\mathcal{P}^{0,*}_{j,(S_h,F_l)},\mathcal{P}^{0,*}_{j,(S_h,F_h)}\right)=\left(\frac{1}{4},\frac{1}{4},\frac{1}{4},\frac{1}{4}\right),$$

where $\Psi^+=2^{\frac{a(1+c)}{\lambda\mu_j}}$, $\Psi=2^{\frac{a-b}{\lambda\mu_j}}$, $\Psi^-=2^{\frac{-2b}{\lambda\mu_j}}$, *and* $\Theta=\Psi^++2\Psi+\Psi^-$.

The optimal amount of attention devoted to a plot with joint input use and the associated expected return are given as

$$\kappa^*_j(\lambda)=2+\frac{\Psi^+}{\Theta}\log_2\left(\frac{\Psi^+}{\Theta}\right)+2\frac{\Psi}{\Theta}\log_2\left(\frac{\Psi}{\Theta}\right)+\frac{\Psi^-}{\Theta}\log_2\left(\frac{\Psi^-}{\Theta}\right)$$

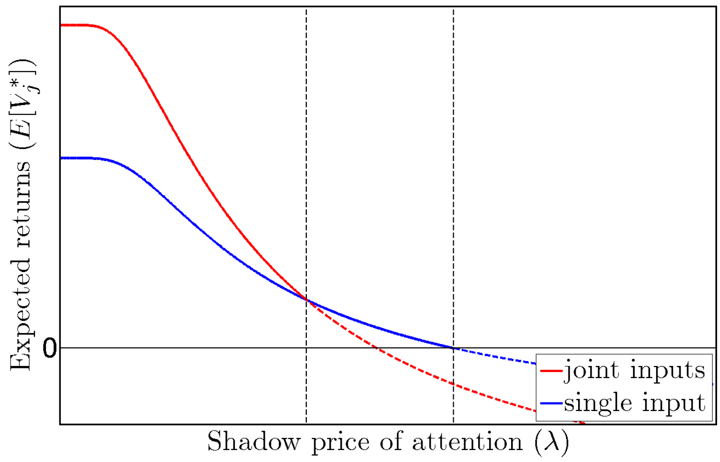
$$E[V_j(\kappa^*_j)]=\Theta^{-1}\left[a(1+c)\,2^{\frac{a(1+c)}{\lambda\mu_j}}+2\cdot(a-b)2^{\frac{a-b}{\lambda\mu_j}}-2b\,2^{\frac{-2b}{\lambda\mu_j}}\right]$$

Proof. See Appendix A. □

Proposition 3 implies that combining multiple inputs on a plot is only optimal if the farmer also allocates a sufficiently large amount of attention to the plot. This is graphically illustrated in Figure 3, which plots the solution of $E[V_j(\kappa^*_j)]$ under joint input use for arbitrarily fixed parameters and different values of λ, and sets it in relation with the corresponding values for single input use. For small values of λ (i.e., attention is abundantly available), the expected payoff is larger for joint input use (red line) than for use of a single input (blue line). Intuitively, this follows from the fact that with enough attention, the farmer is able to apply both inputs adequately and take advantage of their complementarity.

For larger values of λ (i.e., attention is sufficiently scarce), the farmer is better off by applying only a single input (right of the first vertical reference line) or switching to non-adoption (second reference line). The reason for this is that while combining modern inputs offers potentially larger returns (e.g., due to their complementarity), the obtained payoffs are also more sensitive to the chosen practices. Combining inputs in a profitable way thus tends to require more attention then using only a single input. In particular, under joint input use the farmer has to reduce uncertainty about both elements of the

Figure 3: Expected returns for joint and single input use



Note: Simulations based on varying $\overline{\kappa}$ for fixed parameter values $(a, b, c, R, \mu) = (1, 2, 0.7, 0, 1)$.

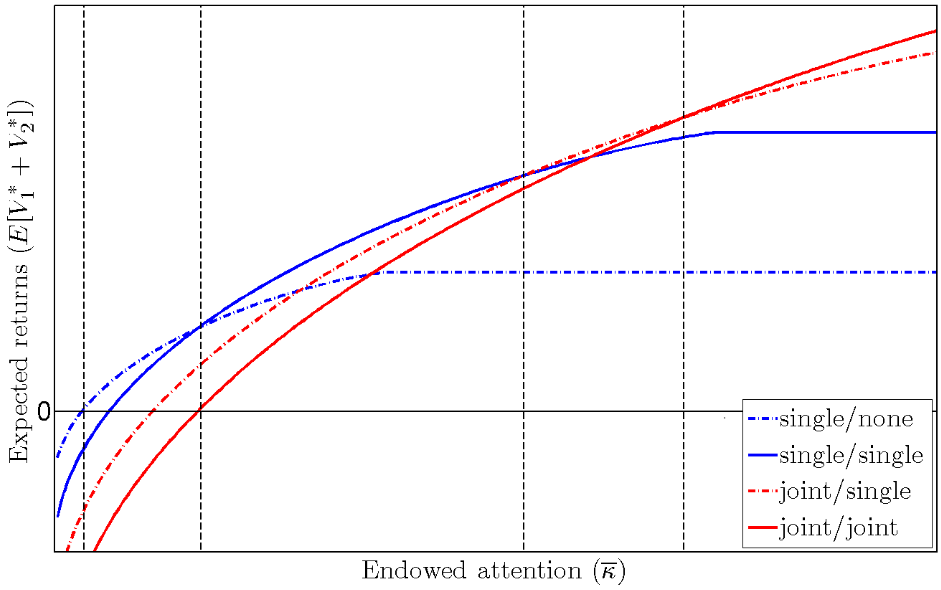
state (e.g., l and h for the state (l, h)), while for single input use the farmer has to be attentive only to one of the two elements (only the first element if he uses S and only the second element if he uses F).

Optimal behavior across two plots. The farmer's overall input choice behavior is illustrated in Figure 4, which depicts the expected returns of different input combinations across two plots for different values of endowed attention $\overline{\kappa}$ and fixed parameter values. As indicated by the intersections of the different graphs, there is no generally dominant action, but the optimal behavior depends on the farmer's scarcity of attention. For very small values of $\overline{\kappa}$ (corresponding to large values of λ), the farmer optimally chooses not to adopt any modern inputs (left of the first vertical reference line). This is due to the fact that without enough attention, the farmer is unable to sufficiently reduce the risk of selecting inadequate input practices.

If the amount of available attention is larger, input choices that require more attention, but also offer potentially higher returns, are optimal. In the example depicted in Figure 4, as $\overline{\kappa}$ increases it first becomes optimal to apply a single modern input on one plot (first reference line), then on both plots (second reference line), and eventually to jointly apply both inputs on one plot (third reference line) and then on both plots (fourth reference line).[25] In particular, this also implies that farmers who have access to complementary inputs may optimally choose to apply these inputs separately (i.e., spread them across

[25]The exact order is sensitive to parameter values (particularly with regard to the possibility of combining two inputs on one plot and using no input on the other plot; see Step 4 in Appendix A). However, the result that higher opportunity cost of attention tends to make less complex input combinations optimal, is a general feature that emerges from the model's underlying structure (including the parameter restrictions described in Section 2.1).

Figure 4: Optimal input choice behavior for two plots



Note: Simulations based on varying $\overline{\kappa}$ for fixed parameter values $(a, b, c, R, \mu_1, \mu_2) = (1, 2, 0.7, 0, 1, 1)$.

plots), if the available amount of attention is not enough to make joint input use profitable in expectation.

The mechanism illustrated in Figure 4 also gives rise to the prediction that farmers may optimally decide to opt in and out of using modern inputs over time, or vary the degree to which they combine complementary inputs on the same plots. To see this, one can consider a simple dynamic extension of the model in which the decision problem of the farmer in each period is given by the (static) optimization problem as stated in Section 2.3. If the state of the world is uncorrelated over time and there is variation in λ across periods (e.g., in some periods the farmer faces more distractions or more demanding decisions than in other periods), then optimal behavior will change over time. The farmer will thus adjust his input practices across periods. Notice that this holds even if the general profitability of using modern inputs remains constant (i.e., independent of fluctuations in prices and returns).

2.5 Farmer heterogeneity and external interventions

I now use the model to study how changes in the cost of information processing will affect farmers' input choices. In the model, the marginal cost of processing information is captured by the parameter μ.[26] The following focuses on differences in μ across farmers

[26]Since this section focuses on heterogeneity at the household level, the results are derived for the case where μ_j is identical across plots of the same farmer (subscript j is thus dropped in the following).

that stem from factors at the household level which determine how much attention a farmer needs to absorb and evaluate information about plot states and associated optimal cultivation practices. This allows for two possible interpretations. First, differences in μ may reflect heterogeneity in farmer characteristics which determine how costly it is for the farmer to process information, such as education, experience, and access to certain infrastructure or technology. For example, μ may be smaller for farmers who are literate or have access to agricultural mobile phone apps and online tools, because this will tend to make it easier for them to reduce uncertainty about how to optimally apply modern inputs given current conditions. In addition, changes in μ may also capture the effect of external interventions which help farmers in choosing better cultivation practices. This may include weather forecasts, official recommendations (e.g., based on regional soil and pest analysis), and other forms of agricultural advisory services. Irrespective of the source of changes in the cost of information processing, the effect on optimal input decisions in the model can be summarized as follows.

Corollary 1. *Farmers who face a lower cost μ of processing information (e.g., due to household characteristics or external interventions) are more likely to adopt modern inputs and to combine complementary inputs on the same plots.*

Proof. See Appendix B. □

Intuitively, smaller values of μ make it less costly for the farmer to reduce uncertainty about how to optimally apply modern inputs. This decreases the amount of attention that is needed to use modern inputs in a profitable way (i.e., to generate higher expected returns than those of non-adoption). In addition, reductions in μ also lower the threshold in attention that is required to make combining multiple inputs profitable in expectation. According to the model, lower cost of information processing will thus facilitate both uptake and joint usage of modern inputs.

2.6 Summary of predictions

Summarizing, the model gives rise to the following predictions:

(i) Even when farmers have access to profitable modern inputs and are aware of their benefits, they may optimally choose not to adopt these inputs.

(ii) Even when farmers have access to complementary inputs and using these inputs jointly is profitable under adequate practices, farmers may optimally choose to spread inputs across plots rather than combining them.

(iii) Farmers who have adopted modern inputs will apply these in varying ways (e.g. timing and quantity), trying to adapt to the underlying conditions. In doing so, farmers will occasionally choose suboptimal practices, including in the long run.

(iv) Farmers who use modern inputs will pay due attention to the conditions on their plots. In doing so, farmers will tend to devote more attention to complex input combinations, i.e. those for which returns are very sensitive to present conditions.

(v) When farmers are compared that are similar along other characteristics, those who face a lower opportunity cost of attention, or smaller cost of processing information about adequate cultivation practices (e.g., due to experience or access to helpful technology), will be more likely to adopt and combine modern inputs.

(vi) Interventions that reduce the mental effort for farmers to process information about optimal input practices will increase uptake and joint usage of modern inputs. In particular, such interventions will tend to be more effective than programs which only provide farmers with access to the same information.

(vii) Even when external conditions that affect the profitability of modern inputs (e.g., prices or transaction costs) do not significantly change, farmers may optimally decide to switch in and out of using modern inputs, or vary the degree to which they combine inputs on the same plots.

3 Empirical evidence

Some predictions of the model correspond well with the 'stylized facts' about agricultural input use in Sub-Saharan Africa. In particular, predictions (i) and (iii) conform with the large body of empirical evidence on persistently low adoption rates of modern inputs in African agriculture, as well as farmers' suboptimal input practices given adoption (World Bank, 2007; Duflo et al., 2008; Hanna et al., 2014; Binswanger and Savastano, 2017).[27] There also exists ample evidence on post-adoption switching behavior (prediction (vii)), particularly with regard to use of inorganic fertilizer and hybrid seeds (Dercon and Christiaensen, 2011; Duflo et al., 2011; Suri, 2011). Furthermore, prediction (vi) is supported by the findings of recent field experiments, which provide evidence for an important role of attention constraints in affecting input practices in the development context (Cole and Fernando, 2013; Beaman et al., 2014; Casaburi et al., 2014; Hanna et al., 2014). In particular, these studies show that providing farmers and other micro-entrepreneurs with relevant information in pre-processed form (e.g., based on personalized

[27]While recent data suggests that for some African countries the share of farmers using modern inputs has started to increase during past years, usage rates still tend to be very low relative to other regions in the world (Sheahan and Barrett, 2017).

reminders and advice via mobile phones) improves behavior significantly more than solely providing access to the same information.

Predictions (iv) and (v) of the model cannot readily be tested, since there is currently no adequate data available on farmers' allocation of attention and associated mental opportunity cost. However, future research may be able to assess the empirical plausibility of predictions (iv) and (v) based on adequate field experiments.[28]

Prediction (ii) is of particular interest, since it is contrary to the implications of existing models in the context of agricultural input use (see discussion in Section 4). According to the emerging evidence on important agronomic synergies between modern inputs such as improved seeds, fertilizer, and other agrochemicals, farmers that behave efficiently should pair these inputs together on the same plots (Morris et al., 2007; Sheahan et al., 2013; Nyangena and Juma, 2014).[29] In contrast to the expectation, Prediction (ii) suggests that farmers may rationally decide to abstain from this (otherwise optimal) behavior, if constraints on attention hinder them from reducing uncertainty about adequate ways of combining inputs with each other. Prediction (ii) thus offers a possibility to distinguish the identified mechanism from other channels proposed in the economic literature to account for low adoption rates of modern inputs.

As recently noted by Sheahan and Barrett (2017), there exists relative little empirical evidence on within-farm allocation of complementary inputs across individual plots. In order to verify Prediction (ii) of the model and to shed some light on joint input use in general, I now turn to an empirical analysis of agricultural input decisions in Sub-Saharan Africa. The focus of the analysis is to explore in how far households that are already using complementary inputs on their farms (i.e., those that have evidently overcome the major barriers to adoption), are also combining these inputs together on the same plots. This differs from most existing studies in the context of agricultural technology adoption, which typically focus on identifying those factors that determine farmers' initial decision to adopt (individual) modern inputs.[30]

3.1 Data and variables

The analysis is based on four nationally representative datasets of farmers in Malawi, Nigeria, Tanzania, and Uganda. These were collected between 2012 and 2016 as part of the Living Standard Measurement Study - Integrated Surveys on Agriculture (World

[28]To test prediction (iv), it would in principle be sufficient to collect quantitative data on farmers' allocation of attention (e.g., based on similar tools as in time use surveys). To test prediction (v), future research could consider the design of field experiments which are able to elicit exogenous variation in farmers' mental opportunity cost, and investigate to what extent this affects input choices. For example, such experiments could be based on "attentional interventions" similar to those implemented by Hanna et al. (2014) and Beaman et al. (2014).

[29]See also references listed in footnote 2.

[30]Most studies in this context focus on adoption decisions at the household rather than the plot level.

Bank, 2016). For most of the analysis, I pool the information from all four datasets, such that the overall sample includes 11,289 observations at the household (farm) level and 22,726 observations at the plot level. This includes all households in the original LSMS-ISA dataset that cultivated at least one plot during the main agricultural season in each country (plots that are rented out or left fallow are excluded).

Table 4 in the appendix provides a list of the used variables, along with basic summary statistics. The main variables of interest are plot-level indicators for use of modern inputs. The observed inputs are improved seeds, inorganic fertilizer (referred to as 'fertilizer' in the following), other agrochemicals (mainly pesticides and herbicides), organic fertilizer ('manure'), and irrigation systems. All of these variables capture binary usage decisions for individual plots (the analysis does not consider intensity of application).[31] Based on the variables for individual inputs, indicators are constructed that capture joint use of pairs of complementary inputs or sets of three inputs. In addition, plot-level information is aggregated at the household level to obtain indicators for modern input use on farm. These indicators are set equal to one if the respective inputs are used on any of the plots cultivated by a household in the given season (irrespective of how inputs are allocated across plots).

The LSMS-ISA dataset also contains rich information about demographics, both at the plot and household level. As shown in Table 4, this includes farm size, number of cultivated plots, distance to the nearest road or market, as well as further household characteristics such as education, age, gender of the household head, and exposure to extension services. At the plot level, I observe size, ownership status, and a number of farmer-assessed plot characteristics such as soil quality, slope, and erosion.

3.2 Results

Concerning adoption rates of individual inputs, the mean values provided in Table 4 show that there is considerable heterogeneity between countries, but adoption rates generally remain at relatively low levels (conforming with prediction (i) of the model). The highest rate is observed for inorganic fertilizer use in Malawi (57 percent of plots). While in Nigeria 39 percent of plots receive fertilizer, in Tanzania and Uganda the share is only 11 and 3 percent, respectively (this corresponds roughly to the findings of other studies in this context, see Binswanger and Savastano, 2017; Sheahan and Barrett, 2017). For improved seeds, adoption rates at the plot level range between 11 percent in Uganda and 42 percent in Malawi. A range of similar magnitude is also observed for use of agrochemicals, where the highest rate of 42 percent is attained in Nigeria. Use of organic

[31] Although the LSMS-ISA project seeks to collect data in a comparable way, the available information on some inputs differs slightly across countries. More details on the construction of variables in these cases are provided in Appendix C.

Table 2: Joint input use at the farm and plot level

	Fertilizer		Improved seeds		Agro-chemicals		Manure		Irrigation	
	Farm	Plot	Farm	Plot	Farm	Plot	Farm	Plot	Farm	Plot
Pairwise use:										
Improved seeds	18.1	10.5								
Agrochemicals	10.1	7.1	5.4	3.2						
Manure	10.3	6.5	7.5	3.7	5.1	3.2				
Irrigation	1.1	0.6	0.9	0.4	0.8	0.4	0.7	0.3		
Sets of three inputs:										
Fertilizer, Impr. seeds					3.5	1.8	5.0	2.1	0.6	0.3
Fertilizer, Agrochem.							3.5	2.2	0.7	0.4
Fertilizer, Manure									0.4	0.2
Unconditional mean	37.4	29.0	29.7	22.0	19.0	15.4	19.8	13.6	2.0	1.2
Observations	11,269	22,680	10,960	20,687	11,270	22,678	11,272	22,686	11,285	22,712

Notes: All percentages are based on binary input decisions. Unconditional means report the share of farms or plots in the sample on which the individual input in the respective column is used. Plots that are rented out or left fallow are excluded. *Source:* Author's calculations based on pooled data from the Living Standards Measurement Study - Integrated Surveys on Agriculture: Malawi 2013, Nigeria 2015/16, Tanzania 2012/13, Uganda 2013/14.

fertilizer ranges between 6 percent of plots in Uganda and 23 percent of plots in Nigeria. The least used input appears to be irrigation systems, which are only present on about 1 to 2 percent of plots in all countries.

As a first step to explore the extent to which farmers combine modern inputs with each other, Table 2 shows joint usage rates for all possible pairs of observed inputs as well as sets of three inputs involving fertilizer and improved seeds.[32] For each combination, joint usage rates are calculated both at the farm and plot level. Unconditional means reported at the bottom of the table indicate the share of farms or plots in the sample on which the input in the respective column is used. Overall, Table 2 indicates that in the four considered countries modern inputs are rarely applied together. As shown in the first column, only 18 percent of households use improved seeds and fertilizer jointly on their farm, and 10 percent combine fertilizer with other agrochemicals or manure, respectively. At the plot level, less than half of the 22 percent of plots that are cultivated with improved seeds also receive fertilizer (10.5 percent), and less than a sixth receive other agrochemicals (3.2 percent). Not surprising, the degree to which inputs are combined becomes even smaller when looking at sets of three inputs. For all considered combinations, at most 5 percent of households use three inputs together on their farms (namely fertilizer, improved seeds, and manure). At the plot level, the maximal share drops to 2.2 percent for joint use of

[32] These combinations represent sets of inputs which are typically perceived as generating important agronomic synergies when applied together on the same plots (Morris et al., 2007; Sheahan and Barrett, 2017).

Table 3: Plot-level use conditional on modern inputs being used on farm

Number of inputs	Any input (1)	Fertilizer (2)	Improved Seeds (3)	Agrochemicals (4)	Irrigation (5)
None	28.3	16.8	21.0	18.4	23.4
One	46.1	44.3	42.6	40.0	31.0
Two	22.5	33.9	30.8	32.8	22.9
Three or more	3.1	5.0	5.6	8.8	22.7
Observations	14,807	8,976	7,159	4,851	546

Notes: Percentages are conditional on households using at least one input on their farm, as specified in each column (i.e., excluding plots that are cultivated by farmers who use no modern input in column (1), and those who do not use the input specified in columns (2) to (5), respectively). Plots that are rented out or left fallow are excluded. *Source:* Author's calculations based on pooled data from the Living Standards Measurement Study - Integrated Surveys on Agriculture: Malawi 2013, Nigeria 2015/16, Tanzania 2012/13, Uganda 2013/14.

fertilizer, improved seeds, and agrochemicals.

It is important to note that in principle these low numbers could be accounted for by any of the explanations for low adoption rates of (individual) modern inputs discussed in the economic literature (e.g., lack of knowledge or risk aversion). This applies less to the results reported in Table 3 and Table 5 (Appendix D), which show joint usage rates at the plot level conditional on households using modern inputs on the farm. This means that only plots are included that are cultivated by households which generally have access to modern agricultural inputs, are aware of them, and willing to apply them on their farms.[33] As the percentages in the first column of Table 3 show, households that already use at least one modern input on their farm combine inputs only on a quarter of plots, while 28 percent of plots are cultivated without any modern inputs. Similar values are also obtained when conditioning on specific modern inputs (columns 2 to 5). For example, less than 40 percent of plots cultivated by farmers who have adopted fertilizer also receive a second complementary input, and only 5 percent of these plots are cultivated with combinations of three inputs. When looking at pairs of complementary inputs and plots cultivated by households that use both respective inputs together on their farm, still around 40 to 55 percent of plots do not receive both inputs jointly (see Table 5 in Appendix D). Similar results are also obtained when restricting the analysis to plots that are cultivated with maize as the main crop (Table 6 in Appendix D).[34] Overall, these

[33]The results in Table 3 follow the approach of Sheahan and Barrett (2017), who report joint usage rates conditional on households using at least one modern input. Table 5 in the appendix reports adoption rates for sets of inputs conditional on households using all of the respective inputs on their farm.

[34]While some input complementarities may be independent of crops (e.g., fertilizer and irrigation), the size of the associated efficiency gains is likely to vary across crops. Maize is known both to respond relatively strong to individual modern inputs (e.g., fertilizer), and to feature important synergy effects

findings conform with predictions (i) and (ii) of the model.
In order to provide some more insights into farmers' decision to combine modern inputs, Table 7 (Appendix D) reports mean values of household and plot characteristics for subsets of plots cultivated with different numbers of modern inputs.[35] The results indicate that plots which receive combinations of multiple modern inputs tend to be cultivated by larger farms than plots which receive only one or no modern input (both in terms of area and household size). In addition, plots under joint input use are more likely to belong to households that are closer located to roads and markets, feature higher education as well as a male household head, and have access to agricultural extension services. When looking at plot characteristics, plots that receive more modern inputs tend to be larger and are more often planted with maize. Plot ownership status and other farmer-reported characteristics such as soil quality, slope, and erosion are on average relative similar across the considered groups of plots. While some of these findings seem to be in line with predictions (v) and (vi) of the model, it is important to note that these could also be related to other channels that affect farmers' input decisions. The next section discusses the most important alternative theories in this context.

4 Alternative explanations

As noted above, the predictions of the model coincide with empirical observations of agricultural input decisions in Africa, including many findings of other studies in this context. This section reviews alternative channels that are frequently considered for explaining low adoption rates of modern agricultural inputs, and discusses to what extent these are able to generate similar qualitative predictions as those listed in Section 2.6.

Imperfect markets and profitability. Authors that follow the traditional view of farmers as rational profit maximizers often suggest explanations for low adoption rates that focus on low profitability of modern agricultural inputs and on imperfect markets in developing countries. This includes theories based on insecure land ownership, credit constraints, and imperfect insurance in the presence of risk-aversion (Moser and Barrett, 2006; Dercon and Christiaensen, 2011; Karlan et al., 2014), as well as other factors that directly affect the profitability of modern inputs (Suri, 2011; Bold et al., 2017).
While many of the proposed channels in this stream of literature are supported by empirical evidence, they are only able to account for part of the observed patterns in modern input use in Sub-Saharan Africa. In particular, theories that perceive farmers as rational

under combined input use, in particular related to improved seed varieties and fertilizer (Morris et al., 2007; Sheahan et al., 2013; MacRobert et al., 2014; Nyangena and Juma, 2014).

[35] The results in Table 7 are purely descriptive and should not be interpreted as evidence for causal relationships.

profit maximizers with perfect information tend to be unable to account for occasional mistakes in input usage (prediction (iii)) and for significant effects of purely attention-related interventions (prediction (vi)). In addition, these theories are almost exclusively based on factors at the household level. While such factors may determine whether farmers are generally able and willing to adopt certain inputs on their farms (prediction (i)), they tend to be unsuited to account for plot-level differences in joint input use, particularly for households that have already adopted these inputs on their farms (prediction (ii)).

Behavioral biases. Another body of literature in this context focuses on deviations from fully rational behavior and stresses the role of behavioral biases in explaining low adoption rates. This is often based on the view that modern inputs (e.g., fertilizer and other agrochemicals) represent divisible technologies that offer large returns at such small investment levels that even the poorest households can afford. Some authors therefore argue that traditional explanations, such as credit constraints and risk-aversion, are unable to account for persistently low adoption rates in these contexts, because households should be able to gradually increase their investments into these technologies (Udry, 2010; Banerjee and Duflo, 2005, 2012). For example, summarizing evidence on low fertilizer use, Datta and Mullainathan (2014) come to the conclusion that "fertilizer is available, affordable, effective, and appreciated. But it is still not used by farmers." In response to this puzzling finding, authors have suggested behavioral biases, such as procrastination, limited self-control, and imperfect prospective memory, to explain imperfect technology adoption behavior (Bertrand et al., 2004; Duflo et al., 2011; Datta and Mullainathan, 2014). In addition to their ability to explain non-adoption and fluctuations in modern input use (predictions (i) and (vii)), these models are in principle also able to account for occasional mistakes in input usage (prediction (iii)) as well as the observation that factors which do not directly affect the profitability of modern inputs can have significant effects on farmers' input choices (predictions (v) and (vi)).

An important finding in this context is presented by Duflo et al. (2011), who show that small time-limited discounts for fertilizer right after the previous harvest (i.e., vouchers for free delivery in the so-called SAFI program) increase adoption of fertilizer by about the same extent as large price subsidies later in the season. Contrary to the predictions of most standard models, this indicates that the timing of price discounts is more important than the magnitude. The authors interpret this as evidence for an important role of procrastination, where vouchers represent a commitment device for farmers to overcome time-inconsistent behavior. While this interpretation seems convincing, the results might also allow for an alternative interpretation following the perspective of imperfect attention. As Duflo et al. (2011) briefly mention, the visits by field officers in the SAFI program may have reduced the time for farmers to think about which type and quantity of fertilizer to use, because they were offered a simple option and required to make an immediate decision. This feature, together with the finding of Mani et al. (2013) that farmers tend to have larger attentional capacity at the end of harvest, suggests that these field visits might have resulted in a stronger response by farmers at the time right after harvest than later in the season independent of the offered intervention (i.e., free delivery or price subsidy).[36] Although speculative, the rational inattention approach may thus offer an additional channel through which the SAFI program might have affected farmers' decision to adopt fertilizer.[37]

Learning. A large body of literature that seeks to explain empirical patterns of agricultural technology adoption focuses on learning (Besley and Case, 1993; Foster and Rosenzweig, 1995; Jovanovic and Nyarko, 1996; Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010). The underlying idea of these models is that farmers do initially not know how to use modern inputs correctly. Learning is perceived as gathering information based on previous outcomes, either through individual experimentation ('learning by doing') or by knowledge spillovers from others ('social learning'). This allows agents to refine their knowledge about optimal actions and thus increases the incentives to adopt.

While learning models also emphasize the importance of uncertainty about optimal ways of using technology, they differ from the rational inattention approach in at least three important ways.[38] First, learning models seek to explain imperfect adoption behavior based on limited availability of information, while the bottleneck in the rational inattention approach are constraints in information processing. Therefore, standard learning models are unable to account for prediction (vi).[39]

Second, in learning models agents update beliefs about a fixed target value (recall that in the model in Section 2, agents process information about a stochastic variable that determines optimal actions). Therefore, learning models typically generate the feature that agents' knowledge about optimal actions increases monotonically over time, as more and more data becomes available (provided there is perfect recall). These models are thus better suited to explain imperfect input choices for new technologies (e.g., in the case of recently developed hybrid seeds during the Green Revolution in India, or a newly introduced crop as in Conley and Udry, 2010). In the long-run, however, most learning models are unable to account for non-adoption of profitable modern inputs (prediction (i)), suboptimal cultivation practices (predictions (ii) and (iii)), and switching behavior

[36] Mani et al. (2013) find a direct negative effect of poverty on cognitive function. In particular, they show that farmers perform worse on attention-related tasks before harvest (i.e, when they are poor) than at the end of harvest (when relatively rich).

[37] In order to distinguish between the partial effects of the SAFI program through the channels of attention and procrastination, future research may incorporate both channels into a single dynamic framework and derive testable predictions about the respective quantitative roles.

[38] For a more detailed discussion of the relationship between learning models and rational inattention models of technology adoption see Naeher (2017).

[39] An exception is the model by Hanna et al. (2014), which combines learning with imperfect attention.

(prediction (vii)).[40] It is important to note that in the context of modern input use in African agriculture today, modern inputs have been available for several decades and feature a long history of large-scale extension work through governments and NGOs. Several authors therefore conclude that learning seems unlikely to be an important driver of imperfect adoption decisions in this context (Duflo et al., 2010, 2011; Suri, 2011).

Third, in learning models updating beliefs is usually based solely on data that has been generated by previous outcomes. In contrast, the rational inattention approach models the idea that farmers have to be attentive to changes in the underlying conditions in order to choose optimal actions. In particular, this implies that the need to be attentive to current conditions remains in the long-run (i.e., it is not sufficient to rely on past experience). One implication of this difference for extension programs is that it may not be sufficient to teach farmers once how to use modern inputs, but a more continuous form of support that is tailored to the individual environment in which farmers operate may be needed to promote efficient input use.

Alternative concepts of attention. It should be noted that the use of the term 'attention' is not always unambiguous in the economic literature. While rational inattention models typically focus on inattention to certain pieces of *information*, other authors have also used the term to refer to inattention to *actions*. This concept corresponds to the idea of imperfect prospective memory commonly studied in psychology, and has only recently started to become the focus of economists (Ericson, 2011; Taubinsky, 2013; Haushofer, 2014).[41] Another concept frequently associated with attention is imperfect recall of information (also referred to as imperfect retrospective memory), where people are unable to fully remember previously known information from the past (Mullainathan, 2002; Ericson, 2017). Furthermore, attention has been modeled as a stimulus-driven allocation process, emphasizing the importance of salient aspects of different pieces of information over the true value they carry (Bordalo et al., 2013; Kőszegi and Szeidl, 2013). In these models, attention allocation is exogenous to the decision maker and determined by external signals rather than by optimizing behavior.[42]

[40] By combining learning and imperfect attention, the model of Hanna et al. (2014) is able to explain why agents may persistently fail to make optimal decisions about some input dimensions.

[41] Inattention to actions describes the phenomenon that people often form clear intentions of how to act in the future, but then absent-mindedly fail to carry out these actions, because they simply forget about them. This results in time-inconsistent behavior and introduces a potential need for simple reminders and uninformative attention cues, such as alarm-clocks.

[42] For a more detailed overview of concepts of attention used in economics, see Hefti and Heinke (2015).

5 Conclusion

This paper develops a new framework to study agricultural input decisions in the presence of complementarities. The critical feature of the model is that farmers face a limited capacity to process information and are therefore unable to be perfectly attentive to specific field and seasonal conditions on all their plots. In line with empirical evidence on the limits of human cognition, I demonstrate how the model can explain why farmers may optimally decide not to combine complementary inputs on the same plots or abstain from adopting profitable inputs in the first place.[43]

Bringing the model to the data shows that the predictions of the identified mechanism are consistent with many stylized facts of modern agricultural input use in Sub-Saharan Africa. In particular, the model offers a possible explanation for persistently low adoption rates and can account for the observation that farmers use adopted inputs in suboptimal ways, including spreading complementary inputs across plots instead of combining them (Sheahan and Barrett, 2017). The model can also account for post-adoption switching behavior in modern input use, such as frequently observed for fertilizer and hybrid seeds (Dercon and Christiaensen, 2011; Duflo et al., 2011; Suri, 2011). Furthermore, the model generates testable predictions about the link between attention-related variables and farmers' input decisions.

Due to insufficient data on farmers' allocation of attention, the direct evidence on the identified mechanism is currently very limited. Any statement about the quantitative role of the proposed attention channel would therefore be speculative. I thus do not wish to argue that the mechanism derived in this paper constitutes the primary force behind farmers' input choices. Rather, I suggest that it can complement the insights of existing models in this context and should be considered as an additional channel to contribute to explanations of empirical patterns in agricultural input use.

The paper also contributes to the growing body of literature that stresses the role of attention constraints for economic decision-making. While most of this literature has focused primarily on applications in rich countries, several reasons suggest that imperfect attention may be particularly relevant in the context of poor economies.[44] First, the poor often have less access to information in pre-processed form (e.g., through online search tools) and to distraction-saving goods and services (such as stable electricity and water

[43]This includes evidence on the limits of human cognition in general (DellaVigna, 2009; Beaman et al., 2014; Hanna et al., 2014; Bartoš et al., 2016) as well as evidence particularly on rational inattention (Caplin and Dean, 2013; Gabaix et al., 2006; Goecke et al., 2013).

[44]To my knowledge, this is the first application of rational inattention in the development context. Initially, applications of rational inattention focused primarily 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). More recent studies expand the analysis to other fields, including finance (Kacperczyk et al., 2016), industrial organization (Martin, 2017), and labor (Acharya and Wee, 2016). In the development context, some papers study the role of other forms of imperfect attention (Beaman et al., 2014; Hanna et al., 2014).

supply) than people in the developed world (Banerjee and Mullainathan, 2008). This tends to increase the amount of attention that is needed to make well-informed choices and thus exacerbates the severity of limitations to cognitive capacity which all humans face. In addition, an increasing body of evidence suggests that there may exist a direct adverse effect of poverty on cognitive functioning, because poverty-related concerns can induce stress thereby consume mental resources (Mani et al., 2013; Haushofer and Fehr, 2014).

In total, the paper suggests a more nuanced approach to agricultural policies aimed at promoting uptake and efficient use of modern inputs. If the decision of farmers to adopt and combine modern inputs is critically affected by the mental cost associated with processing information about optimal ways of using these inputs, then policies and extension programs might optimize their impact by using information and attention-related interventions to complement approaches which are purely based on monetary incentives (such as price subsidies). This is in line with recent initiatives to improve the provision of pre-processed agricultural information, making use of economies of scale in data collection and processing as well as cost-effective ways of delivering real-time advice using modern information and communication technology (Fabregas et al., 2017). Following the implications of the model, such programs should focus on providing guidance which is tailored to farmers' individual growing conditions (rather than general 'best practices'), take into account seasonal changes, and convey information in forms that minimize the required attentional effort for farmers.

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APPENDIX

A Proof of Propositions 1 - 3

This appendix derives the farmer's optimal strategy in four steps. First, I transform the decision problem given by (4) - (4.3) into an equivalent problem which is based on state-contingent choice probabilities instead of signals. This allows for an analytical solution for each possible action on a single plot, which is obtained in the second step. The third step derives the agent's optimal behavior for a single plot. The last step uses the results to obtain the optimal behavior across two plots.

Step 1: Reformulated decision problem.

Following the approach suggested by Matějka and McKay (2015), the solution to the discrete choice problem given by equations (4) - (4.3) can be derived as the solution to the following reformulated optimization problem:

$$\max_{\left\{\mathcal{P}_{j,k}(\mathrm{v})\right\}_{k\in\mathcal{K}}} \sum_{j=1}^{2}\sum_{k\in\mathcal{K}}\int_{V} v_{j,k}\mathcal{P}_{j,k}(\mathrm{v})G(dV) \tag{A.1}$$

$$\text{s.t.} \quad H(k) - E_{\mathrm{v}}\left[H(k \mid \mathrm{v}_j)\right] \leq \kappa_j \quad \forall j \tag{A.2}$$

$$\sum_{j=1}^{2}\mu_j\kappa_j \leq \overline{\kappa} \tag{A.3}$$

$$\sum_{k\in\mathcal{K}}\mathcal{P}_{j,k}(\mathrm{v}) = 1 \qquad \forall j \tag{A.4}$$

In the transformed problem, the solution is given by the set of conditional probabilities $\{\mathcal{P}_{j,k}(\mathrm{v})\}_{k\in\mathcal{K}}$ for each plot that maximizes the sum of expected payoffs from the two plots subject to the given constraints. If attention is abundantly available, restrictions (A.2) and (A.3) are not binding. In this special case (which corresponds to a model with perfect information), the farmer is perfectly attentive to all of his plots and thus able to select the action with the highest return with probability one for each plot. As follows from the payoffs specified in Table 1, in this case the farmer optimally applies both inputs jointly in order to take advantage of the agronomic synergies.

If attention is scarce, conditions (A.2) and (A.3) must hold with equality, since otherwise attention would be wasted. Using the mathematical definition of entropy in condition (A.2), the amount of attention allocated to plot j can be written as

$$\kappa_j = -\sum_{k\in\mathcal{K}} \mathcal{P}^0_{j,k} \log_2 \mathcal{P}^0_{j,k} + \int_V \sum_{k\in\mathcal{K}} \mathcal{P}_{j,k}(\mathrm{v}) \log_2 \mathcal{P}_{j,k}(\mathrm{v}) G(dV). \tag{A.5}$$

Plugging this expression into condition (A.3) yields

$$\overline{\kappa} = -\sum_{j=1}^{2} \mu_j \left(\sum_{k\in\mathcal{K}} \mathcal{P}^0_{j,k} \log_2 \mathcal{P}^0_{j,k} - \int_V \sum_{k\in\mathcal{K}} \mathcal{P}_{j,k}(\mathrm{v}) \log_2 \mathcal{P}_{j,k}(\mathrm{v}) G(dV) \right). \tag{A.6}$$

Equation (A.6) can be used to replace conditions (A.2) and (A.3) in the farmers's decision problem. Solving the corresponding Lagrangian leads to the optimality condition

$$\mathcal{P}^*_{j,k}(\mathrm{v}) = \frac{\mathcal{P}^0_{j,k}\, 2^{v_{j,k}/\lambda\mu_j}}{\sum_{l\in\mathcal{K}} \mathcal{P}^0_{j,l} 2^{v_{j,l}/\lambda\mu_j}}, \tag{A.7}$$

where λ denotes the Lagrange multiplier of condition (A.6). The unconditional probabilities $\mathcal{P}^0_{j,k}$ must be internally consistent in that they fulfill

$$\mathcal{P}^0_{j,k} = \int_V \mathcal{P}_{j,k}(\mathrm{v}) G(dV). \tag{A.8}$$

Substituting the conditional choice probabilities with the expression in equation (A.7) and dividing both sides by $\mathcal{P}^0_{j,k}$ leads to the condition

$$1 = \int_V \frac{2^{v_{j,k}/\lambda\mu_j}}{\sum_{l\in\mathcal{K}} \mathcal{P}^0_{j,l} 2^{v_{j,l}/\lambda\mu_j}} G(dV) \quad \text{ if } \mathcal{P}^0_{j,k} > 0. \tag{A.9}$$

To further simplify the expression and obtain an analytical solution that depends only on the deep parameters of the model, one can focus on a specific choice set and insert the associated distribution of values $v_{j,k}$ into condition (A.9). In the following, I consider each of the three types of possible actions on a single plot separately, before deriving the farmer's optimal input choice behavior across two plots.

Step 2: Optimal choice probabilities for different actions on a single plot.

Non-adoption. If the farmer chooses not to adopt any modern input on plot j, he selects the outside option, $k = (0, 0)$, by setting $\mathcal{P}_{j,(0,0)}(\mathrm{v})$ equal to one for all states and the probabilities of all other actions equal to zero. In this case, the conditional and unconditional probabilities are identical, and the secure return $R = 0$ is realized with certainty. Plugging the probabilities into equation (A.5) shows that the amount of attention allocated to the plot equals zero.

Single input use. As both inputs are assumed to be homogeneous, it is sufficient to derive the optimal probabilities for one of the two inputs. Without loss of generality, let S be the applied input whenever the farmer uses a single input on plot j. Plugging the associated payoffs from Table 1 into equation (A.9) yields the following two conditions:

$$1 = 0.5\,\frac{2^{\frac{a}{\lambda\mu_j}}}{\mathcal{P}^0_{j,(S_l,0)}2^{\frac{a}{\lambda\mu_j}} + \mathcal{P}^0_{j,(S_h,0)}2^{\frac{-b}{\lambda\mu_j}}} + 0.5\,\frac{2^{\frac{-b}{\lambda\mu_j}}}{\mathcal{P}^0_{j,(S_l,0)}2^{\frac{-b}{\lambda\mu_j}} + \mathcal{P}^0_{j,(S_h,0)}2^{\frac{a}{\lambda\mu_j}}} \qquad \text{if } \mathcal{P}^0_{j,(S_l,0)} > 0$$

$$1 = 0.5\,\frac{2^{\frac{-b}{\lambda\mu_j}}}{\mathcal{P}^0_{j,(S_l,0)}2^{\frac{a}{\lambda\mu_j}} + \mathcal{P}^0_{p,(S_h,0)}2^{\frac{-b}{\lambda\mu_j}}} + 0.5\,\frac{2^{\frac{a}{\lambda\mu_j}}}{\mathcal{P}^0_{j,(S_l,0)}2^{\frac{-b}{\lambda\mu_j}} + \mathcal{P}^0_{j,(S_h,0)}2^{\frac{a}{\lambda\mu_j}}} \qquad \text{if } \mathcal{P}^0_{j,(S_h,0)} > 0$$

Since $\mathcal{P}^0_{j,(S_l,0)}$ and $\mathcal{P}^0_{j,(S_h,0)}$ must sum up to one, there are three possible solutions to this pair of equations. One where both unconditional probabilities are greater than zero, and the two cases where either $\mathcal{P}^0_{j,(S_l,0)}$ or $\mathcal{P}^0_{j,(S_h,0)}$ is equal to zero and the other probability is equal to one, respectively. In the first case, combining the two conditions leads to

$$0 = \frac{2^{\frac{a}{\lambda\mu_j}} - 2^{\frac{-b}{\lambda\mu_j}}}{\mathcal{P}^0_{j,(S_l,0)}2^{\frac{a}{\lambda\mu_j}} + \mathcal{P}^0_{j,(S_h,0)}2^{\frac{-b}{\lambda\mu_j}}} + \frac{2^{\frac{-b}{\lambda\mu_j}} - 2^{\frac{a}{\lambda\mu_j}}}{\mathcal{P}^0_{j,(S_l,0)}2^{\frac{-b}{\lambda\mu_j}} + \mathcal{P}^0_{j,(S_h,0)}2^{\frac{a}{\lambda\mu_j}}}.$$

Expanding both fractions to the common denominator and simplifying the expression yields

$$0 = \left(2^{\frac{a}{\lambda\mu_j}} - 2^{\frac{-b}{\lambda\mu_j}}\right)^2 \left(\mathcal{P}^0_{j,(S_h,0)} - \mathcal{P}^0_{j,(S_l,0)}\right). \tag{A.10}$$

Since $a, b > 0$, equation (A.10) only holds for $\mathcal{P}^0_{j,(S_h,0)} = \mathcal{P}^0_{j,(S_l,0)}$. It thus follows that

$$\left(\mathcal{P}^{0,*}_{j,(S_l,0)}, \mathcal{P}^{0,*}_{j,(S_h,0)}\right) = \left(\frac{1}{2}, \frac{1}{2}\right), \text{ whenever } \mathcal{P}^0_{j,(S_l,0)}, \mathcal{P}^0_{j,(S_h,0)} > 0. \tag{A.11}$$

The two other possible cases correspond to situations in which one of the two options is chosen directly (i.e., without processing any information). Based on the returns specified in Table 1, the expected value of such a strategy would be dominated by the outside option. Therefore, the probabilities in equation (A.11) represent the unique solution for a plot under single input use.

Based on this result, the optimal choice probabilities $\mathcal{P}^*_{j,k}(\mathrm{v})$ can be obtained by plugging the solution for $\mathcal{P}^{0,*}_{j,k}$ into equation (A.7). This directly gives the expression stated in Proposition 2.

The solution for κ_j^* can be found by plugging the optimal probabilities $\mathcal{P}^*_{j,k}(\mathrm{v})$ and $\mathcal{P}^{0,*}_{j,k}$ into equation (A.5). This leads to

$$\begin{aligned}
\kappa_j^* = & -0.5\log_2(0.5) - 0.5\log_2(0.5)\\
& + 0.5\left[\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}}\log_2\left(\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}}\right)+\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}}\log_2\left(\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}}\right)\right]\\
& + 0.5\left[\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}}\log_2\left(\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}}\right)+\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}}\log_2\left(\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}}\right)\right],
\end{aligned}$$

which can be simplified to the expression stated in Proposition 2:

$$\kappa_j^* = 1+\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}}\log_2\left(\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}}\right)+\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}}\log_2\left(\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}}\right).$$

In a similar way, the optimal probabilities can be used to derive an expression for the expected return on a plot with single input use, which is defined in the farmer's optimization problem (A.1) as

$$E[V_j(\kappa_j)] = \sum_{k\in\mathcal{K}}\int_V v_{j,k}\mathcal{P}_{j,k}(\mathrm{v})G(dV). \tag{A.12}$$

Plugging $\mathcal{P}^*_{j,k}(\mathrm{v})$ and $\mathcal{P}^{0,*}_{j,k}$ into equation (A.12) leads to

$$E[V_j(\kappa_j^*)] = 0.5\,a\,\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}} - 0.5\,b\,\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}} - 0.5\,b\,\frac{2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}} + 0.5\,a\,\frac{2^{\frac{a}{\lambda\mu_j}}}{2^{\frac{-b}{\lambda\mu_j}}+2^{\frac{a}{\lambda\mu_j}}}.$$

Further simplifying the equation leads to the expression stated in Proposition 2:

$$E[V_j(\kappa_j^*)] = \frac{a\,2^{\frac{a}{\lambda\mu_j}} - b\,2^{\frac{-b}{\lambda\mu_j}}}{2^{\frac{a}{\lambda\mu_j}}+2^{\frac{-b}{\lambda\mu_j}}}.$$

This concludes the proof of Proposition 2. □

Joint input use. The optimal probabilities for joint input use on plot j can be derived along the same lines as in the case of single input use. Plugging the corresponding payoffs from Table 1 into the optimality condition (A.9) yields four conditions, one for each of the four possible ways of applying both inputs together. For the first action, $k = (S_l, F_l)$, the condition reads

$$\begin{aligned}
1 = 0.25\, &\frac{\Psi^+}{\mathcal{P}^0_{j,(S_l,F_l)}\Psi^+ + \mathcal{P}^0_{j,(S_l,F_h)}\Psi + \mathcal{P}^0_{j,(S_h,F_l)}\Psi + \mathcal{P}^0_{j,(S_h,F_h)}\Psi^-} \\
+ 0.25\, &\frac{\Psi}{\mathcal{P}^0_{j,(S_l,F_l)}\Psi + \mathcal{P}^0_{j,(S_l,F_h)}\Psi^+ + \mathcal{P}^0_{j,(S_h,F_l)}\Psi^- + \mathcal{P}^0_{j,(S_h,F_h)}\Psi} \\
+ 0.25\, &\frac{\Psi}{\mathcal{P}^0_{j,(S_l,F_l)}\Psi + \mathcal{P}^0_{j,(S_l,F_h)}\Psi^- + \mathcal{P}^0_{j,(S_h,F_l)}\Psi^+ + \mathcal{P}^0_{j,(S_h,F_h)}\Psi} \\
+ 0.25\, &\frac{\Psi^-}{\mathcal{P}^0_{j,(S_l,F_l)}\Psi^- + \mathcal{P}^0_{j,(S_l,F_h)}\Psi + \mathcal{P}^0_{j,(S_h,F_l)}\Psi + \mathcal{P}^0_{j,(S_h,F_h)}\Psi^+} \qquad \text{if } \mathcal{P}^0_{j,(S_l,F_l)} > 0, \qquad \text{(A.13)}
\end{aligned}$$

where $\Psi^+ = 2^{\frac{a(1+c)}{\lambda\mu_j}}$, $\Psi = 2^{\frac{a-b}{\lambda\mu_j}}$, and $\Psi^- = 2^{\frac{-2b}{\lambda\mu_j}}$. For the other three possible actions, the respective conditions are given by analogous terms. The solution to the system of equations given by these four conditions is obtained by assigning equal probabilities $\mathcal{P}^0_{j,k}$ to each of the four actions. This can be shown by verifying the guess

$$\left(\mathcal{P}^{0,*}_{j,(S_l,F_l)}, \mathcal{P}^{0,*}_{j,(S_l,F_h)}, \mathcal{P}^{0,*}_{j,(S_h,F_l)}, \mathcal{P}^{0,*}_{j,(S_h,F_h)}\right) = \left(\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}\right), \qquad \text{(A.14)}$$

as outlined in the following. Plugging the presumed values into equation (A.13) and simplifying the obtained expression leads to

$$\begin{aligned}
1 = 0.25\, &\frac{\Psi^+}{\frac{1}{4}\Psi^+ + \frac{1}{4}\Psi + \frac{1}{4}\Psi + \frac{1}{4}\Psi^-} + 0.25\, \frac{\Psi}{\frac{1}{4}\Psi + \frac{1}{4}\Psi^+ + \frac{1}{4}\Psi^- + \frac{1}{4}\Psi} \\
+ 0.25\, &\frac{\Psi}{\frac{1}{4}\Psi + \frac{1}{4}\Psi^- + \frac{1}{4}\Psi^+ + \frac{1}{4}\Psi} + 0.25\, \frac{\Psi^-}{\frac{1}{4}\Psi^- + \frac{1}{4}\Psi + \frac{1}{4}\Psi + \frac{1}{4}\Psi^+}.
\end{aligned}$$

Further simplifying the equation shows that this is equivalent to

$$1 = \frac{\Psi^+ + 2\Psi + \Psi^-}{\Psi^+ + 2\Psi + \Psi^-}. \qquad \text{(A.15)}$$

In the same way, the guess can be verified for the other three conditions. Therefore, if the farmer decides to use both inputs together on a plot, each possible way of combining the two inputs optimally features the same unconditional probability of being selected.[45] Based on this result, the optimal choice probabilities $\mathcal{P}^*_{j,k}(\mathrm{v})$ can be obtained by plugging the solution for $\mathcal{P}^{0,*}_{j,k}$ into equation (A.7). This directly gives the expression stated in Proposition 3.

[45]The uniqueness of the solution follows from the results in Online Appendix C of Matějka and McKay (2015), for which the problem considered here represents a special case.

The solution for κ_j^* under joint input use can be obtained by plugging the corresponding optimal probabilities $\mathcal{P}_{j,k}^*(\mathrm{v})$ and $\mathcal{P}_{j,k}^{0,*}$ into equation (A.5). This leads to

$$\kappa_j^* = -\,4\left[\frac{1}{4}\log_2\left(\frac{1}{4}\right)\right] + \frac{\Psi^+}{\Psi^+ + 2\Psi + \Psi^-}\log_2\left(\frac{\Psi^+}{\Psi^+ + 2\Psi + \Psi^-}\right)$$
$$+\,2\frac{\Psi}{\Psi^+ + 2\Psi + \Psi^-}\log_2\left(\frac{\Psi}{\Psi^+ + 2\Psi + \Psi^-}\right) + \frac{\Psi^-}{\Psi^+ + 2\Psi + \Psi^-}\log_2\left(\frac{\Psi^-}{\Psi^+ + 2\Psi + \Psi^-}\right)$$

Simplifying the equation leads to the expression provided in Proposition 3:

$$\kappa_j^*(\lambda) = 2 + \frac{\Psi^+}{\Theta}\log_2\left(\frac{\Psi^+}{\Theta}\right) + 2\frac{\Psi}{\Theta}\log_2\left(\frac{\Psi}{\Theta}\right) + \frac{\Psi^-}{\Theta}\log_2\left(\frac{\Psi^-}{\Theta}\right)$$

where $\Theta = 2^{\frac{a(1+c)}{\lambda\mu_j}} + 2\cdot 2^{\frac{a-b}{\lambda\mu_j}} + 2^{\frac{-2b}{\lambda\mu_j}}$. In a similar way, the optimal probabilities can be used to derive the expected return of a plot with joint input use. Plugging $\mathcal{P}_{j,k}^*(\mathrm{v})$ and $\mathcal{P}_{j,k}^{0,*}$ into the corresponding part of the farmer's objective function (A.1) shows that

$$E[V_j(\kappa_j^*)] = \frac{a(1+c)\;2^{\frac{a(1+c)}{\lambda\mu_j}}}{\Theta} + 2\frac{(a-b)\;2^{\frac{a-b}{\lambda\mu_j}}}{\Theta} - \frac{2b\;2^{\frac{-2b}{\lambda\mu_j}}}{\Theta}.$$

This concludes the proof of Proposition 3. $\square$

Step 3: Optimal input choice behavior for a single plot.

To derive the farmer's behavior for a single plot, first notice that the optimal allocation of attention and associated expected payoff depend on the opportunity cost of attention, captured by the Lagrange multiplier λ. For fixed parameter values (a, b, c, R, μ_1, μ_2), the size of λ is determined by the amount of endowed attention $\overline{\kappa}$. To see this, one can insert the corresponding expressions for κ_1^* and κ_2^* from Propositions 2 and 3 into the budget constraint of attention (A.3), which yields an equation that contains only λ, $\overline{\kappa}$, and the deep parameters of the model. This feature can be used to show that the agent's optimal behavior is characterized by a number of cutoff values for $\overline{\kappa}$, which determine whether non-adoption, single input use, or joint input use on a plot is optimal for given parameter values.

Consider first the choice between non-adoption and single input use. The existence of a unique threshold in attention that determines which of the two actions is optimal follows from three properties. First, as shown below, the expected payoff of single input use is monotonically increasing in $\overline{\kappa}$. Second, if $\overline{\kappa} = 0$, the expected return of using the input is smaller than the secure return of the outside option. This follows directly from the payoffs specified in Table 1 and the assumption that $0 < a < b$. Third, for sufficiently large values of $\overline{\kappa}$ the expected payoff of single input use is larger than that of non-adoption. In particular, under perfect attention (i.e., $\overline{\kappa}$ large enough so that λ equals zero) the agent can select the optimal option with certainty, such that the realized payoff is $a > 0$. This implies that there is exactly one value for $\overline{\kappa}$ at which the expected payoff of single input use and of non-adoption cross. Let this threshold be denoted as $\overline{\kappa}(c_1)$. For values of $\overline{\kappa}$ smaller than $\overline{\kappa}(c_1)$, the agent prefers the outside option. If $\overline{\kappa}$ is larger than $\overline{\kappa}(c_1)$, the agent uses (at least) a single input on the plot.

Next consider the choice between single and joint input use. Under the made assumption that $c < 2\frac{b}{a} - 1$, the expected return of combining inputs without paying any attention to the plot is smaller than the expected return of using a single input (see last column in Table 1). On the other hand, if $\overline{\kappa}$ is sufficiently large, the expected payoff for joint input use is larger than for single input use. This follows under perfect attention, where the realized payoff under joint input use equals $a(1+c) > a$. Again, it can be shown that the expected payoff of joint input use is monotonically increasing in $\overline{\kappa}$ (see below). This implies that there is a unique value for $\overline{\kappa}$ at which the expected payoff of joint input use and single input use cross. Let this threshold be denoted as $\overline{\kappa}(c_2)$. It captures the minimal amount of endowed attention for which combining two inputs on a plot yields a larger expected payoff than single input use.

It should be noted that if the second cutoff lies below the first one, the farmer may switch from non-adoption directly to joint input use as $\overline{\kappa}$ increases (such that using a single input is never optimal). This may arise if single input use is relatively unattractive (i.e. even for large values of $\overline{\kappa}$ the expected return is only slightly larger than the secure payoff of the outside option), and joint input use is relatively attractive (e.g., because c is large). In order to be able to capture the full spectrum of farmers' input choices, I focus on the case where $\overline{\kappa}(c_2) > \overline{\kappa}(c_1)$.

Before deriving the optimal behavior across two plots, the monotonicity of expected payoffs with respect to scarcity of attention can be derived as follows. For single input use, the expected payoff is given in Proposition 2. Dividing both numerator and denominator by $2^{\frac{a}{\lambda\mu_j}}$ leads to

$$E[V_j(\kappa_j^*)] = \frac{a - b\,2^{\frac{-(a+b)}{\lambda\mu_j}}}{1 + 2^{\frac{-(a+b)}{\lambda\mu_j}}}.$$

Taking the first derivative with respect to λ and simplifying the resulting expression yields

$$\frac{\partial E[V_j(\kappa_j^*)]}{\partial \lambda} = -\frac{(a+b)^2 \ln(2)}{\lambda^2 \mu_j} 2^{\frac{-(a+b)}{\lambda\mu_j}} \left(1 + 2^{\frac{-(a+b)}{\lambda\mu_j}}\right)^{-2} \tag{A.16}$$

As the derivative is negative (recall that $a, b, \mu_j > 0$), the expected payoff of single input use is monotonically decreasing in λ.

For joint input use, the expected payoff is given in Proposition 3 as

$$E[V_j(\kappa_j^*)] = \underbrace{\frac{a(1+c)}{\Theta}\, 2^{\frac{a(1+c)}{\lambda\mu_j}}}_{(A)} \underbrace{+2\frac{(a-b)}{\Theta}\, 2^{\frac{a-b}{\lambda\mu_j}}}_{(B)} \underbrace{-\frac{2b}{\Theta}\, 2^{\frac{-2b}{\lambda\mu_j}}}_{(C)}, \tag{A.17}$$

where $\Theta = 2^{\frac{a(1+c)}{\lambda\mu_j}} + 2\cdot 2^{\frac{a-b}{\lambda\mu_j}} + 2^{\frac{-2b}{\lambda\mu_j}}$. The derivative with respect to λ can be computed as the sum of derivatives of the three summands. These are given by

$$\frac{\partial(A)}{\partial\lambda} = \left[-\frac{a^2(1+c)^2\ln(2)}{\lambda^2\mu_j}\, 2^{\frac{a(1+c)}{\lambda\mu_j}}\,\Theta - a(1+c)\, 2^{\frac{a(1+c)}{\lambda\mu_j}}\,\Theta'\right]\Theta^{-2} \tag{A.18}$$

$$\frac{\partial(B)}{\partial\lambda} = \left[-\frac{2(a-b)^2\ln(2)}{\lambda^2\mu_j}\, 2^{\frac{a-b}{\lambda\mu_j}}\,\Theta - 2(a-b)\, 2^{\frac{a-b}{\lambda\mu_j}}\,\Theta'\right]\Theta^{-2} \tag{A.19}$$

$$\frac{\partial(C)}{\partial\lambda} = \left[-\frac{4b^2\ln(2)}{\lambda^2\mu_j}\, 2^{\frac{-2b}{\lambda\mu_j}}\,\Theta + 2b\, 2^{\frac{-2b}{\lambda\mu_j}}\,\Theta'\right]\Theta^{-2}, \tag{A.20}$$

where Θ' denotes the derivative of Θ with respect to λ

$$\frac{\partial\Theta}{\partial\lambda} = -\frac{a(1+c)\ln(2)}{\lambda^2\mu_j} 2^{\frac{a(1+c)}{\lambda\mu_j}} - \frac{2(a-b)\ln(2)}{\lambda^2\mu_j} 2^{\frac{a-b}{\lambda\mu_j}} + \frac{2b\ln(2)}{\lambda^2\mu_j} 2^{\frac{-2b}{\lambda\mu_j}}. \tag{A.21}$$

For the derivative of the first term (A), it can easily be verified that the term in squared brackets is negative (simplifying leads to a sum in which each term is negative). Since the remaining factor Θ^{-2} is positive, it follows that $\frac{\partial(A)}{\partial\lambda} < 0$.
For the derivative of the second term (B), inserting Θ and Θ' and simplifying the resulting expression leads to

$$\frac{\partial(B)}{\partial\lambda} = \frac{2(a-b)(b+ac)\ln(2)}{\lambda^2\mu_j}\, 2^{\frac{(a-b)+a(1+c)}{\lambda\mu_j}} + \frac{2(b^2-a^2)\ln(2)}{\lambda^2\mu_j}\, 2^{\frac{-2b+(a-b)}{\lambda\mu_j}}. \tag{A.22}$$

In a similar way, the derivative of the third term (C) can be written as

$$\frac{\partial(C)}{\partial\lambda} = -\frac{2b\,[2b+a(1+c)]\ln(2)}{\lambda^2\mu_j}\, 2^{\frac{-2b+a(1+c)}{\lambda\mu_j}} - \frac{4b(a+b)\ln(2)}{\lambda^2\mu_j}\, 2^{\frac{-2b+(a-b)}{\lambda\mu_j}}. \tag{A.23}$$

Since $b > a$, the first fraction in equation (A.22) is negative while the second fraction is positive. In equation (A.23), both fractions are negative such that $\frac{\partial(C)}{\partial\lambda} < 0$. In order to show that the overall derivative of equation (A.17) is negative, one can take the sum of the second (only positive) summand in equation (A.22) and the second summand in equation (A.23). As both are multiplied with the term $2^{\frac{-2b+(a-b)}{\lambda\mu_j}}$, the resulting sum is

$$\left[\frac{2(b^2-a^2)\ln(2)}{\lambda^2\mu_j} - \frac{4b(a+b)\ln(2)}{\lambda^2\mu_j}\right] 2^{\frac{-2b+(a-b)}{\lambda\mu_j}}. \tag{A.24}$$

Simplifying leads to a negative expression

$$-\frac{2(a+b)^2\ln(2)}{\lambda^2\mu_j}\,2^{\frac{-2b+(a-b)}{\lambda\mu_j}} < 0. \tag{A.25}$$

Based on these results, the derivative of equation (A.17) with respect to λ is negative. Therefore, the expected payoff of joint input use is monotonically decreasing in λ (and thus increasing in $\overline{\kappa}$).

Step 4: Optimal behavior across two plots.

For two identical plots, the same amount of attention is needed on each plot to make single input use more attractive than non-adoption, and joint input use more attractive than single input use, respectively. Hence, $\overline{\kappa}$ has to equal at least $2\overline{\kappa}(c_1)$ to make using a single input on both plots desirable. For values smaller than $2\overline{\kappa}(c_1)$, the farmer either adopts the input only on one plot or uses no modern input at all. In the same way, $\overline{\kappa}$ has to equal at least $2\overline{\kappa}(c_2)$ to make joint input use desirable on both plots.
Therefore, as long as $\overline{\kappa}(c_2) > \overline{\kappa}(c_1)$, this implies the following order of optimal actions. For $\overline{\kappa} = 0$, the agent adopts no modern input. As $\overline{\kappa}$ increases, it first becomes optimal to use a single modern input on one plot (i.e., when $\overline{\kappa} = \overline{\kappa}(c_1)$) and then on both plots ($\overline{\kappa} = 2\overline{\kappa}(c_1)$). For larger values of $\overline{\kappa}$ it eventually becomes optimal to apply two inputs on one plot and a single input on the other plot ($\overline{\kappa} = \overline{\kappa}(c_2)+\overline{\kappa}(c_1)$), and then to jointly apply two inputs on both plots ($\overline{\kappa} = 2\overline{\kappa}(c_2)$). Whether it first becomes optimal to apply a single input on both plots or joint inputs on one plot and no input on the other plot depends on the relation of the two cutoff values, i.e. whether $\overline{\kappa}(c_2) > 2\overline{\kappa}(c_1)$. This concludes the proof of Proposition 1. $\square$

B Proof of Corollary 1

In the case of identical plots ($\mu_j = \mu$), the budget constraint for attention (4.3) is given as

$$\mu(\kappa_1 + \kappa_2) \leq \overline{\kappa}. \tag{B.1}$$

For fixed endowment of attention $\overline{\kappa}$, a reduction in μ thus increases the amount of attention ($\kappa_1 + \kappa_2$) that is available to reduce uncertainty about plot states according to condition (4.2). Analogous to an increase in $\overline{\kappa}$ itself, this makes attention in the farmer's decision problem less scarce and thus lowers the associated shadow price λ. Using the results derived in Appendix A (Step 3), it follows that the expected payoffs for single and joint input use are increasing for smaller values of μ. Holding the payoff under non-adoption fixed, this implies that the threshold in available attention $\overline{\kappa}(c_1)$ that is needed to make using modern inputs on a plot profitable is lowered if μ decreases.

For sufficiently large reductions in μ, this also lowers the second cutoff $\overline{\kappa}(c_2)$ at which combining inputs on a plot becomes more attractive than single input use. This follows from the fact that for fixed $\overline{\kappa}$, values of μ sufficiently close to zero allow for arbitrarily large reductions in uncertainty (as the sum of κ_1 and κ_2 in condition (B.1) increases), and the feature that payoffs are such that under perfect attention combining inputs is more profitable than single input use (e.g., due to complementarity). As plots are identical, these insights carry over to the case of two plots according to the results in Appendix A (Step 4). $\square$

C Data and variables

This appendix describes the construction of variables for the unique questionnaire design in each country. Whenever possible, I followed the approach of other studies based on the LSMS-ISA database (Deininger et al., 2017; Binswanger and Savastano, 2017; Sheahan and Barrett, 2017).

Plots and farm size. In Malawi, Nigeria, and Tanzania, data on area of cultivated land and most inputs is collected for plots. For Uganda, the corresponding unit of land is a parcel, so all respective values are aggregated across plots on a parcel. FOr the purpose of the analysis, farm size and number of plots include only plots that are cultivated by the household in a given season. Depending on the country, this excludes pasture and forest land as well as plots that are left fallow and given or rented out.

Fertilizer. For all countries, the indicator is based on a binary response by farmers whether they used any 'inorganic/chemical fertilizer' on the respective plot or parcel.

Improved seeds. Several earlier rounds of the LSMS-ISA surveys include information about seed types only for those seeds that were purchased by farmers in the same season. While this has been changed for the most recent waves in all countries which are used in the analysis, a few differences still remain: In Uganda, the distinction is only made between 'traditional' and 'improved' seeds. In Tanzania, the questionnaire contains a third category for 'improved recycled' seeds, which I do not include in the indicator variable. In Nigeria, the indicator lumps together 'improved' and 'hybrid' seeds. In Malawi, the distinction between improved and traditional seeds is only possible for maize, tobacco, groundnuts, and rice (comprising about 80 percent of plots). The corresponding adoption rate for Malawi should therefore be seen as a lower bound.

Agrochemicals. For Malawi and Tanzania, the indicator is based on a binary response by farmers whether they used any 'pesticide/herbicide' on the respective plot. For Nigeria, the indicator is based on two individual questions about use of pesticide and herbicide. In Uganda, the respective survey question contains only pesticides, but later refers to it as 'pesticides/herbicides'.

Manure. For all countries, the indicator is based on a binary response by farmers whether they used any 'organic fertilizer' on the respective plot or parcel (possibly including types of organic fertilizer other than manure).

Irrigation. For all countries, the indicator is based on farmers' responses whether the plot was irrigated.

Table 4: List of variables

Variable	Full sample[a]	Malawi 2013	Nigeria 2015/16	Tanzania 2012/13	Uganda 2013/14	Description[b]
Farm level:						
Farm size	1.50	0.79	1.88	2.19	1.09	Cultivated area, farmer-assessed (ha)
Plots	2.17	2.08	2.07	2.32	2.24	Number of cultivated plots
Members	5.75	5.28	6.26	5.67	5.85	Number of household members
Distance to road	12.71	9.05	7.09	21.67	-	Distance to road (km)
Distance to market	58.7	23.53	71.23	82.34	-	Distance to market (km)
Rural	0.86	0.87	0.89	0.84	0.86	Rural household (D)
Education						Highest education in household:
no schooling	0.07	0.04	0.15	0.05	0.03	Never attended school (D)
primary	0.49	0.57	0.24	0.62	0.53	Primary or Quaranic school (D)
secondary	0.38	0.35	0.47	0.31	0.41	Secondary school (D)
tertiary	0.06	0.04	0.15	0.02	0.03	Higher education, university (D)
Male head	0.77	0.76	0.84	0.77	0.69	Head of household is male (D)
Age head	48.2	43.93	53.15	48.85	46.96	Age of household head
Age median	21.68	19.91	24.13	22.72	19.72	Median age of household
Extension	0.19	0.37	0.10	0.08	0.20	Received advice in last 12 months (D)
Observations (max.)	**11,289**	**3,038**	**2,834**	**3,023**	**2,394**	
Plot level:						
Plot size	0.75	0.39	0.94	1.08	0.56	Size of plot, farmer-assessed (ha)
Good soil	0.59	0.47	0.81	0.45	0.65	Good soil quality, farmer-assessed (D)
Sloped	0.35	0.41	0.25	0.30	0.43	Plot is sloped (D)
Erosion	0.17	0.36	0.06	0.10	0.12	Plot has problems with erosion (D)
Owned	0.83	0.87	0.84	0.83	0.77	Plot is owned by household (D)
Land title	0.11	0.03	0.07	0.16	0.23	Household has land title for plot (D)
Maize	0.38	0.66	0.16	0.41	0.22	Main crop on plot is maize (D)
Fertilizer	0.29	0.57	0.39	0.11	0.03	Inorganic fertilizer used on plot (D)
Improved seeds	0.22	0.42	0.14	0.19	0.11	Improved seeds used on plot (D)
Agrochemicals	0.15	0.04	0.42	0.10	0.06	Agrochemicals used on plot (D)
Manure	0.14	0.13	0.23	0.12	0.06	Organic fertilizer used on plot (D)
Irrigation	0.01	0.01	0.01	0.02	0.01	Plot is irrigated (D)
Observations (max.)	**22,726**	**6,231**	**5,673**	**6,124**	**4,698**	

Notes: [a] The full sample is obtained by pooling the data from all four countries. [b] (D) indicates dummy variables. Only agricultural plots cultivated by the household are included (i.e., not rented out or left fallow). *Source:* Author's computation based on the Living Standards Measurement Study - Integrated Surveys on Agriculture (World Bank, 2016).

D Additional tables

Table 5: Plot-level use conditional on all inputs being used on farm

Inputs	Any two inputs (1)	Fertilizer, Improved seeds (2)	Fertilizer, Agrochemicals (3)	Fertilizer, Manure (4)	Improved seeds, Agrochemicals (5)
None	16.5	11.1	12.4	18.0	17.1
Single input	37.3	36.2	24.3	25.7	32.2
Both inputs combined	46.3	52.6	63.3	56.3	50.6
Observations	8,181	4,135	2,530	2,610	1,309

Notes: Percentages are conditional on households using two modern inputs together on their farm, as specified in each column (i.e., excluding plots cultivated by farmers who use less than two modern inputs in column (1), and those who do not use both of the inputs in columns (2) to (5), respectively). Plots that are rented out or left fallow are excluded. *Source:* Author's calculations based on pooled data from the Living Standards Measurement Study - Integrated Surveys on Agriculture: Malawi 2013, Nigeria 2015/16, Tanzania 2012/13, Uganda 2013/14.

Table 6: Plot-level use conditional on modern inputs being used on farm (maize plots)

Number of inputs	Any input (1)	Fertilizer (2)	Improved seeds (3)	Agrochemicals (4)	Irrigation (5)
None	14.8	6.2	8.1	13.2	13.8
One	50.3	47.3	40.9	34.4	33.0
Two	31.8	42.2	46.0	38.7	30.5
Three or more	3.1	4.3	5.0	13.7	22.7
Observations	6,472	4,666	3,759	1,322	203

Notes: Percentages are conditional on the household using at least one input on the farm as specified in each column. Only plots on which maize is planted as the main crop are included. *Source:* Author's calculations based on pooled data from the Living Standards Measurement Study - Integrated Surveys on Agriculture: Malawi 2013, Nigeria 2015/16, Tanzania 2012/13, Uganda 2013/14.

Table 7: Household and plot characteristics by number of inputs used on plot

Modern inputs used on plot:	None	One	Two	Three or more	All plots
HH level:					
Farm size	1.81	1.83	1.90	2.18	1.85
Members	5.80	5.96	6.34	7.01	6.00
Distance to road[a]	17.4	11.6	9.6	9.4	13.4
Distance to market[a]	72.2	54.5	46.6	53.5	60.1
Rural	0.90	0.89	0.86	0.89	0.89
Secondary education	0.42	0.49	0.56	0.53	0.47
Male head	0.75	0.80	0.84	0.89	0.79
Age head	49.1	48.2	47.3	47.3	48.4
Age median	21.8	21.3	20.0	18.5	21.2
Extension	0.15	0.22	0.28	0.32	0.20
Plot level:					
Plot size	0.67	0.78	0.81	1.03	0.75
Good soil	0.57	0.59	0.60	0.62	0.59
Sloped	0.34	0.35	0.37	0.30	0.35
Erosion	0.13	0.19	0.22	0.19	0.16
Owned	0.80	0.82	0.79	0.85	0.81
Land title	0.10	0.08	0.08	0.10	0.10
Maize	0.25	0.44	0.62	0.49	0.38
Observations	11,022	6,816	3,673	1,215	22,726

Notes: Mean values for plots cultivated with different numbers of modern inputs. Considered inputs are: improved seed varieties, organic and inorganic fertilizer, other agrochemicals (pesticides/herbicides), and irrigation. [a]Data not available for Uganda.