# How do Zambian smallholder farmers allocate their budget? Evidence of dynamic decision-making based on a Cournot field experiment

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## Abstract

Smallholder farmers in sub-Saharan Africa repeatedly face situations of complex and dynamic decision trade-offs, which include allocating money across short-term and long-term production activities. Short-term activities such as fertilizer application help to cover immediate food needs, but compromise future food production. Long-term production activities, such as building up soil fertility, are important systemic leverage points for future food production, but compromise present-day harvests. This article reports a Cournot field experiment conducted with Zambian farmers to investigate farm management decision-making in a dynamic context with conflicting production objectives. The results revealed that most Zambian smallholder farmers were biased towards short-term production activities, which led to suboptimal performance in production. Despite this bias, the farmers applied various distinct dynamic and non-dynamic decision strategies, with varying production outcomes. Simulation experiments with the decision strategies revealed that most decision strategies resulted in rather stable production patterns. However, following some decision strategies, the production patterns strongly varied when the strategies

interacted with other strategies in the same market and the produce was therefore subject to the strategies' endogenous interactions within the market. Given the farmers' strong preference for fertilizer, the findings suggest that a shift towards favoring long-term oriented production activities is required to increase food production sustainably in sub-Saharan Africa. In conclusion, the various decision strategies and their endogenous interactions reinforce the need for building adaptive capacity among smallholder farmers in order to apply context-specific decision strategies.

# 1. Introduction

Smallholder farmers in sub-Saharan Africa repeatedly face situations of complex and dynamic allocation trade-offs. Should a farmer allocate his or her budget to farm activities that immediately increase food production and compromise sustainable long-term production? Alternatively, should the farmer allocate his or her budget to farm activities that increase food production in the future and tolerate smaller harvests today? The answers to these questions are not trivial, for three reasons. First, the level of food availability is low in sub-Saharan Africa (GFSI, undated) and the immediate need for food may force farmers to focus on short-term production objectives (e.g., through fertilizer purchases). Second, food production systems "memorize" farm decisions through their resources stocks (e.g., soil organic matter), which are an important source of long-term sustainability and resilience (Stave and Kopainsky, 2015). Third, the complexity of the trade-off arises from the dynamic and interlinked nature of farm decisions: whereas budget allocation decisions are restricted to individual farms, the decision outcomes, such as total production, are not restricted in the same way. The aggregated production of individual farms affects the market price, which in turn has an effect on the farm budget for the next growing season and subsequent decisions. Thus, the dynamic nature of such allocation trade-offs and the dynamic environment of the food production system in Zambia mean

that allocation decisions are complex. Additionally, the severity of the decision-making is indicated in the conflicting benefits of short-term and long-term decision alternatives.

Understanding how farmers decide dynamically (i.e., over time) is of central importance to policymakers, agricultural extension officers and food system scholars because farm decisions greatly affect food system outcomes, such as food availability. Low levels of food availability are an enduring challenge in sub-Saharan Africa and even the farmers themselves, who produce the food, are affected by food shortages. The disparity between the continuously growing demand for food on the one side and lagging production on the other side not only results in low food availability, but also depletes the natural resources used in sub-Saharan Africa's food systems (Godfray et al., 2010). Low levels of soil nutrients and soil organic matter, unsustainable water usage, and biodiversity losses all threaten the long-term ability to provide ecosystem services (Foley *et al.*, 2011). Additionally, climate change is likely to cause production losses and yield variability in important crops, such as maize (Lobell *et al.*, 2008). This context highlights the urgent need for approaches that enhance sustainable food production.

The literature on sustainable food production approaches is vast and strategic lines of action that include increasing resource efficiency and closing yield gaps have been summarized; e.g., by Foley *et al.* (2011). Within these strategic lines of action, soil fertility and soil organic matter (SOM) play central roles because they affect agricultural productivity in general and resource efficiency in particular (Kumwenda *et al.*, 1997). Currently, SOM levels are low in sub-Saharan Africa and thus contribute to the big yield gaps. Research has shown that SOM is a systemic leverage point to enhance food production sustainably, and that high levels of stocks such as SOM have the potential to buffer external shocks (Gerber, 2016; Stave and Kopainsky, 2015). However, to increase SOM levels is a long-term process that requires consecutive investments. Since many farmers have short survival-oriented time horizons, Donovan and Casey (1998, p. 25) argue that smallholder farmers "have very high discount rates for future benefits that are far in the future." Consequently, in order to increase short-term food availability, the main focus of

public agricultural policies in many countries in sub-Saharan Africa is to increase the use of inorganic fertilizers through fertilizer subsidy programs (FSPs) (Banful, 2011; Jayne and Rashid, 2013). Whereas fertilizer use in general and FSPs in particular lead to higher levels of food production in the short-term, the application of fertilizers fails to increase SOM stock levels effectively in the long-rung and therefore fails to enhance an important systemic leverage point (Gerber, 2016; Morris *et al.*, 2007). In acknowledging this limitation, governments' and private organizations' policies have focused on conservation agriculture that aims to build up SOM levels. However, despite considerable implementation efforts and the plausible potentials, conservation agriculture has never played a dominant role to the extent that it could have become a real alternative to FSPs (Giller *et al.*, 2009). This reinforces the need for long-term strategies and the need for a better understanding of farmers' decision-making in a dynamic context in order to inform policymakers and agricultural extension officers.

Despite the relevance of understanding farmer' decision-making in a dynamic context, little research has been conducted on sub-Saharan Africa's smallholder farmers' decisions in general and their decisions about recurrent allocation trade-offs in particular (Saldarriaga *et al.*, 2014). Zambia is an exemplary case where food availability is chronically low (GFSI, undated). Many technical, political and social aspects of the Zambian food system have been intensively researched with the aim of increasing food availability: farming practices such as conservation agriculture (e.g., Nyanga, 2012; Umar, 2012), policy interventions such as FSPs (e.g., Jayne and Rashid, 2013; Mason *et al.*, 2013), and health issues that affect food systems such as HIV/AIDS (e.g., Chapoto and Jayne, 2008; Chapoto *et al.*, 2011). However, the literature on farmers' decision-making is restricted to a few topics, such as the adoption of technology (Grabowski *et al.*, 2016; Langyintuo and Mungoma, 2008; Umar, 2014), identification of household decision-makers (Kalinda *et al.*, 2000), production decisions in response to public market interventions (Mason and Jayne, 2013; Mason *et al.*, 2015; Xu *et al.*, 2009), normative decision modeling (Holden, 1993; Katongo, 1986), and static farm expenditure decisions (CSO, 2015). Thus, the dynamic nature of farm budget allocation to production activities in Zambia and

elsewhere in sub-Saharan Africa has largely been overlooked in the literature published to date. This is especially true in cases where farmers face trade-offs between short-term and long-term production objectives. To our knowledge, no study has investigated such budget allocation trade-offs in a dynamic context.

This article contributes to filling the gap in the literature by reporting the application of a dynamic, non-cooperative Cournot oligopoly experiment to the case of smallholder farms in Zambia. In the experiment, the participants (subjects) iteratively decided on how to allocate a given, dynamic budget between two maize production activities: fertilizer purchases (a strategy to enhance maize production the short-term) and the addition of organic matter to the soil (a strategy to enhance maize production in the long run). Unlike other Cournot studies that have mainly contributed to the decision literature on a purely theoretical level, we applied a Cournot experiment to generate empirical evidence about decision-making based on a field experiment with real decision-makers (see Lara-Arango *et al.*, 2017 for conceptual details). A Cournot experiment frame allows decision data to be collected in a dynamic, interactive context. We contribute to existing literature and policy debates in several ways. First, by adapting the standard protocol developed by Huck *et al.* (2004) to the Zambian field setting (i.e., in the absence of a computer network). Second, we corroborated previous assumptions that farmers' decisions are biased towards a short-term strategy (fertilizer use) rather than a long-term strategy (soil improvement). Third, formalized decision heuristics revealed that some farmers decide dynamically based on farm and market information, while others decide on non-dynamic, a priori heuristics. Finally, we tested the heuristics in a dynamic simulation model and found that the performance of some heuristics depended to a large extent on the endogenous interactions with other strategies that are present in the market. Our findings are relevant to decision makers and practitioners as a basis for sustainable policy formulation.

The article is structured as follows. In the next section, were describe the experimental design and procedures. Thereafter, we present the results of the experiments, identify strategies and their heuristics, and analyze the dynamic

implications of the heuristics in terms of performance. Finally, we discuss our findings and draw conclusions based on the results and analyses.

## 2. Experimental design and procedures

## 2.1 Experimental design and setup

We used a semi-computerized experiment based on a Cournot market with non-standard conditions. The setup included five subjects (players), who were not permitted to communicate with one another, in order to avoid collusion. Although our experiment was designed on the basis of a traditional Cournot market, our main interest was to study decision-making by real farmers in an exploratory field experiment (Harrison and List, 2004). Thus, to ensure that the subjects associated the experiment with the situation on their farms, our experiment differed from Huck et al.'s (2004)[1] standard conditions on two structural points (for a detailed discussion of the adjustments to the standard protocol, see Lara-Arango *et al.*, 2017). First, we used a model that was distinctly larger and richer in technical details than other Cournot market experiments (e.g., Arango *et al.*, 2013), in order to make the setting as realistic as possible. Second, we considered a dynamic farm endowment, in which the current budget was determined by the market price and the subject's sales in the previous round, as was the case on real farms.

As a starting point, we used a context-specific, economic system dynamics model of the Zambian maize market—the maize market model, including its theoretical and empirical foundation, which has been described in detail earlier by the first author of the present article (Gerber, 2016)—which we adjusted to the experimental setup. The main adjustments included constant population, constant arable land area, splitting

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[1] Standard conditions: a. Interaction takes place in fixed groups; b. Interaction is repeated over a fixed number of periods; c. Products are perfect substitutes; d. Costs are symmetric; e. There is no communication between players; f. Participants have complete information about their own payoff functions; g. Participants receive feedback about aggregated supply, the resulting price, and their own individual profits; h. The experimental instructions use an economic frame (instructions use economic terms such as "firm," "market," and "price") (Huck et al., 2004, p. 106).

the production sector into five farms (each managed by one subject), and making soil improvement decisions endogenous. Thus, the version of the model used for our study differentiated between sectors that were subject-specific (e.g., the farm sector) and sectors that were general (e.g., the aggregated market), in which the subjects interacted. The parameter values in the study were identical to those in the maize market model described earlier (Gerber 2016), which was calibrated to country-specific data.

A central construct in the experiment was dynamic farm endowment, in which the current budget $B_{i,t}$ for subject i

$$B_{i,t} = P_{t-1} \times Pr_{i,t-1} \times Sps_{i,t-1} \times BSp \tag{1}$$

is determined by the market price $P_{t-1}$, a subject's production $Pr_{i,t-1}$, the share of the subject's production that is sold $Sps_{i,t-1}$ in the previous round (since sub-Saharan Africa's smallholder farmers typically self-consume part of their production) and $BSp$, a constant share of the total farm income that is allocated to two production activities. $BSp$ is set at 0.25. In each round, the subjects decide how to allocate the given budget $B_{i,t}$ to the two production activities "fertilizer purchase" and "organic matter incorporation to the soil" on their farms. The experiment anticipates that the total budget $B_{i,t}$ is allocated to the activities in the form of fertilizer expenditure $ExpF_{i,t}$ and soil improvement expenditure $ExpS_{i,t}$. Soil improvement expenditure $ExpS_{i,t}$ affects the subject's productivity indirectly via SOM and the change of each subject's SOM level $SOM_{i,t}$, which is defined as

$$\frac{dSOM_{i,t}}{dt} = OM_1(y_{i,t}) + OM_2(ExpS_{i,t}, C) - \frac{SOM_{i,t}}{t_{min}} \tag{2}$$

where $OM_1(y_{i,t})$ represents the plant residues of the last season's harvest, which are added to the soil as a function of the subject's yield $y_{i,t}$ and $OM_2(ExpS_{i,t}, C)$

represents the addition of organic matter to the soil. The costs $C$ are set to ZMW[2] 117 per lima[3]. Mineralization is expressed as $\frac{SOM_{i,t}}{t_{min}}$ and represents the process that decomposes SOM and thus reduces SOM levels. The mineralization time $t_{min}$ is set at 31 years. In the mineralization process, plant nutrients are released, taken up by maize plants and contribute to determining yields. The available plant nutrients $x_{i,t}$ are expressed as

$$x_{i,t} = \frac{ExpF_{i,t}}{FP \times AL} + n\left(\frac{SOM_{i,t}}{t_{min}}\right) \tag{3}$$

where $FP$ is the fertilizer price, $AL$ a subject's maize production area, and $n\left(\frac{SOM_{i,t}}{t_{min}}\right)$ is a function that represents the nutrients that are released in the mineralization process. $FP$ is set at ZMW 550 per 50 kg bag and $AL$ is constant at 2 ha for all subjects. The available plant nutrients $x_{i,t}$ are eventually taken up by plants and transformed into maize yield $y_{i,t}$, expressed in 50 kg bags per year per hectare in the following form

$$y_{i,t} = A \times (1 - 10^{-b \times x_{i,t}}) \tag{4}$$

where $A$ is the yield plateau that represents the maximum maize yield under perfect factor availability and $b$ is a model specific constant. $A$ is set at 9 tons per ha per year and $b$ is set to 4.03. The subject's i production $Pr_{i,t}$ is expressed in 50kg bags per year and calculated as follows:

$$Pr_{i,t} = y_{i,t} \times AL \tag{5}$$

The overall market price is calculated as

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[2] Zambian Kwachas, the local currency.

[3] Lima is a local unit used in the measurement of area; 1 lima ≈ 0.25 ha.

$$P_t = \left( \frac{a \times \sum_{i=1}^{5} Pr_{i,t}}{D(Pop)} \right)^{\varepsilon} \times RefP \tag{6}$$

where $a$ is a constant scaling factor, $D(Pop)$ represents the market demand as a function of population, $\varepsilon$ is a price sensitivity parameter set at -0.86 and $RefP$ constitutes a reference market price set at 1 ZMW per kg maize.

To ensure that the model resembled the subjects' own farms as much as possible, we used a more complex version, which comprised additional mechanisms to the key equations presented above. The full model, including all equations and documentation is presented in Appendix C in this dissertation. An overview of the model's core feedback mechanisms is shown in Figure 1.

In terms of dynamic decision-making, fertilizer expenditure constitutes a short-term strategy to increase yields immediately through fertilizer application and nutrient uptake (Figure 1). Soil improvement expenditure represents a long-term strategy that increases yields through building up soil organic matter. Although higher yields increase a farmer's budget for the next growing season through increased production, sales and farm income (R1 and R2 feedback loops, Figure 1), the increased yields also lead to a higher aggregated market supply and thus to a lower price, which in turn leads to lower farm income and a lower budget for the next growing season (B1 feedback loop). In the model show in Figure 1, the B1 loop partly offsets the benefits from the R1 and R2 loops through the subjects' competition. In addition to these market-centered mechanisms, the R3 loop adds plant residues to the SOM stock and plays a central role in the Zambian maize production system because SOM represents a systemic leverage point for increasing food availability and increasing the system's resilience to external shocks, such as changes in rainfall patterns or public policies.
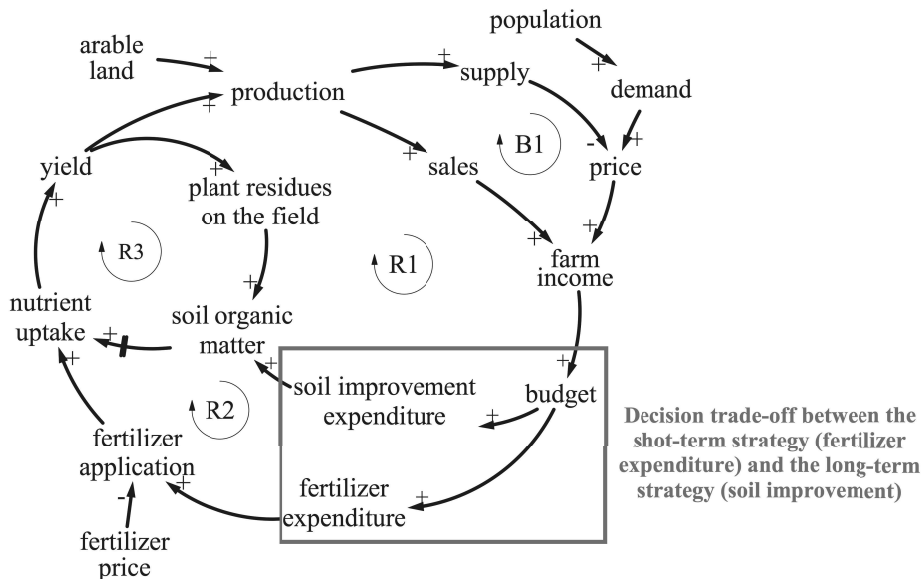
***Figure 1.*** *Causal loop diagram of the system dynamics model.*

*Notes: Arrows indicate causal relationships directed towards the arrowhead. A plus (+) at the arrowhead denotes a positive relationship (where the effect variable changes in the same direction as the cause variable) and a minus (-) denotes a negative causality (where the effect variable changes reversely directed to the cause variable). Feedback loops consist of circular chains of causal relationships and are either reinforcing processes (which self-reinforce the current behavior) or balancing processes (which adjust the behavior towards a goal). R1 – reinforcing soil improvement feedback loop; R2 – reinforcing fertilizer feedback loop; R3 – reinforcing soil organic matter feedback loop; B1 – balancing supply feedback loop.*

The experiment was set to last nine rounds of four years each. In each round, decisions were collected and applied for four years in the simulation model. This allowed experiments to be conducted within a feasible amount of time and still covered a 35-year period, which was long enough for long-term processes such as soil dynamics to unfold. As performance indicator in our experiment, we used the

subject's accumulated production over the total experiment duration because Zambian smallholder farmers maximize production rather than profits (Umar, 2014):

$$Performance_i = \int_0^{35} Pr_{i,t} \ dt \qquad (7)$$

## 2.2 Experimental procedure

Our experiment followed a standard experimental economics protocol, with adjustments to match the rural and cultural context (Huck *et al.*, 2004). The main procedural adjustments were semi-computerized interaction with subjects, lack of structural transparency about the model's equations, no information about aggregated market supply, and physical rewards instead of monetary incentives (Lara-Arango *et al.*, 2017).

Due to varying degrees of literacy among the subjects, a semi-computerized approach was applied, in which experimental instructions were explained verbally in the local language following a standardized protocol (Appendix A). Important parameters to acquaint the subjects with their "experimental farm" (e.g., farm size and costs associated with the decisions) were part of the protocol and were therefore common knowledge, including symmetry across firms. Given the model's complexity and given the varying education levels in rural Zambia, we opted not to inform subjects about the market's mathematical representation. To avoid communication during the experiment, the subjects were spatially separated. For each decision-time point, the subjects received information about the current market price and their own current yield, production level and budget before the budget was allocated to the two expenditure categories: fertilizer and soil improvement. Because the rural context made a fully computerized setting impossible due to the subjects' low degree of familiarity with the use of computers and of outdoor experiments, the information was conveyed to them via record sheets (Appendix B) and communicated verbally. We opted not to inform the subjects about the aggregate market supply because such information is rarely available to Zambian farmers in everyday life. The order of the

provided information was altered from round to round to avoid any order-driven bias. The subjects' decisions were noted and the information later entered into a laptop, and the simulation-based information was conveyed back to the subjects. After the completion of the experiment, a debriefing session helped farmers to reflect on their decision strategy and revealed qualitative information about their decisions. Specially trained field assistants[4] guided the experimental interaction process in the local language. The field assistants helped the subjects to understand the provided information, but strictly avoided advising the subjects on decisions and revealing structural properties of the decision context.

Prior to the experiment, we incentivized the subjects by presenting five standardized, physical rewards that they needed in everyday life,[5] and told them that the subject with best performing farm could choose a reward first, then the second, and so forth until only one reward remained for the last subject. Physical rewards were preferred over monetary rewards because of the legal and cultural context. A "game" with monetary rewards would probably have been interpreted as gambling, for which we would have needed a concession. In addition, such an approach would most likely have distracted the subjects' farming mind-set, which we wanted to analyze. According to Kelly et al. (2015), rewarding based on the performance position within the group acknowledges the subjective normative judgment of different items. The subjects were instructed that their farms' performance would be measured in accumulated production (Equation 7). This reflected Zambian smallholder farmers' production objectives, which mainly focus on covering household needs instead of profit maximization (Umar, 2014). The duration of the experiment was approximately 90 minutes.

The structural and procedural deviations from the standard protocol published by Huck *et al.* (2004) imply that it is not feasible to draw conclusions about the

[4] The field assistants were local people who were trained in three steps: (1) They took part in the experiment as subjects, (2) they made supervised introductions and data collection among themselves, and (3) they were supervised and received feedback in the real experimental setting.

[5] 2 kg sugar, 1 kg sugar, 750 ml cooking oil, big bar of laundry soap and small bar of laundry soap.

rationality of decision-making and thus compare our results with previous studies. Instead, our main contribution lies in the analysis of empirical decisions in a dynamic context.

## 2.3 Subjects

The experiments were conducted in August 2016, in villages around Mumbwa, in Zambia's Central Province, where the main language spoken is Tonga. The subjects were recruited from smallholder farm communities and were either couples or widows who ran farms. Thus, all subjects were real decision-makers on farms. However, they did not have any previous experience of related experiments.

A total of 15 experiments were conducted, with 75 subjects, of whom 50 were couples and the remaining 25 were single. None of the subjects participated in more than one experiment. Through the oral and written communication, we ensured that the subjects understood the farm and market information we gave them. The subjects were motivated to take part in the experiment and made their decisions carefully. Many subjects made calculations on mobile phones or sued pen and paper, or even on sandy soil. From the subjects' reactions during the presentation of the reward items and the award ceremony, it was clear that the physical items had motivated the subjects to perform well. The reward items were chosen in varying orders (e.g., the best performing subject of some experiments chose 2 kg sugar, whereas in other experiments the best performing subject chose 750 ml cooking oil). This indicates differences in subjective normative judgments of the items.

## 2.4 Analysis of decisions

The subjects formulated decisions on fertilizer and soil improvement expenditure in absolute terms, as they would do on their farms in real life. However, the dynamic nature of decision-making, which is a key conceptual element in this article, meant that it was not possible to compare their decisions in absolute terms. The incomparability arose from the dynamic and endogenous interplay between subjects'

decisions; which made one subject's budget dependent on the other subjects' decisions (Equations 1 and 6). Thus, to make the decisions comparable, we analyzed their expenditure relative to their given budget. During the debriefing sessions, some subjects even explicitly expressed that their reasoning behind their decisions was relative, as reflected in statements such as "we balanced the expenditure between the two activities." Thus, in the following analyses we focus on fertilizer expenditure relative to the budget:

$$rEF_{i,t} = \frac{ExpF_{i,t}}{B_{i,t}} \tag{8}$$

where $rEF_{i,t}$ is the relative fertilizer expenditure, and the relative expenditure spent on soil improvement is the remaining share of the budget.

# 3. Results

## 3.1 Fertilizer expenditure decisions of the subjects

We first analyzed the share of the budget allocated to fertilizer and soil improvement, respectively, to find out whether there was a clear tendency towards one of the options. For this initial analysis, the dataset consisted of 675 decisions resulting from 15 markets, with 5 subjects in each market, and 9 decision points over the course of the experiment. The focus in this section is on the general decision-making patterns across all markets and subjects, rather than the results of a detailed analysis of individual markets and time-dependent decisions, which we present later.

The distribution of the 675 decisions is summarized in Figure 2. In 48 cases (7%), the decision was to allocate 30% or less of the budget to fertilizer purchases. In 103 cases (15%), fertilizer expenditure was between 30% and 60% of the budget, and in 524 cases (78%), the fertilizer purchases constituted of 60% or more of the budget. This indicates that the subjects had a tendency to allocate larger amounts of their budget to the short-term option (fertilizer purchases) than to the long-term option (soil improvement).
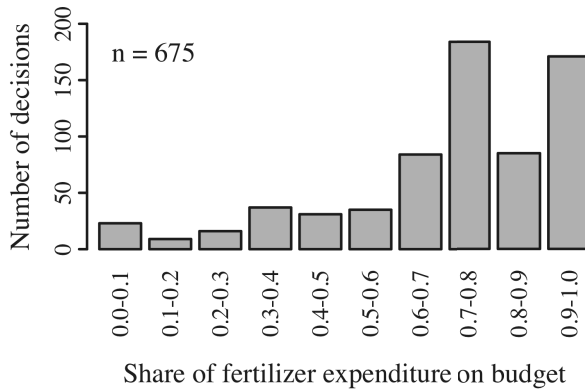
*Figure 2. Distribution of fertilizer decisions.*

To investigate the tendency towards the short-term option further, we analyzed whether there was a systematic bias towards fertilizer expenditure. We conducted two-tailed Mann-Whitney tests to analyze mean differences for the whole sample, the markets and the subjects. The null hypothesis was that the mean relative fertilizer expenditure was equal to 0.5, meaning that subjects in the respective groups had no bias towards one of the expenditure categories:

$$H_0: \mu = 0.5$$

The alternative hypothesis was that subjects in the respective groups were biased towards one of the expenditure categories:

$$H_A: \mu \neq 0.5$$

The results are summarized in Table 1 and they indicate that over the whole sample, subjects were significantly biased towards fertilizer expenditure (p value < 0.01). Additionally, the analysis of the markets revealed that all 15 individual markets showed a significant bias towards fertilizer expenditure (p value < 0.01).

***Table 1.*** *Summary of the fertilizer allocation decisions per market. Indication about bias towards fertilizer is based on Mann-Whitney test.*

| Market (M) | Mean relative fertilizer expenditure | Std. Deviation | Number of decisions | Bias towards fertilizer[a] |
|---|---|---|---|---|
| M1 | 0.75 | 0.240 | 45 | yes *** |
| M2 | 0.69 | 0.233 | 45 | yes *** |
| M3 | 0.69 | 0.263 | 45 | yes *** |
| M4 | 0.59 | 0.319 | 45 | yes *** |
| M5 | 0.73 | 0.220 | 45 | yes *** |
| M6 | 0.57 | 0.362 | 45 | yes *** |
| M7 | 0.85 | 0.133 | 45 | yes *** |
| M8 | 0.71 | 0.184 | 45 | yes *** |
| M9 | 0.77 | 0.182 | 45 | yes *** |
| M10 | 0.64 | 0.253 | 45 | yes *** |
| M11 | 0.84 | 0.182 | 45 | yes *** |
| M12 | 0.68 | 0.207 | 45 | yes *** |
| M13 | 0.69 | 0.134 | 45 | yes *** |
| M14 | 0.74 | 0.177 | 45 | yes *** |
| M15 | 0.81 | 0.133 | 45 | yes *** |
| Totals | 0.72 | 0.237 | 675 | yes *** |

Notes: [a] Significance levels: *** $p < 0.01$, two-tailed; ** $p < 0.05$, two-tailed; * $p < 0.1$, two-tailed.

While the market analysis revealed a clear bias towards fertilizer purchases, the Mann-Whitney test of the individual subjects' decisions revealed a more nuanced picture: The mean value of the relative fertilizer expenditure of 60 subjects (80%) was significantly higher than 0.5, which indicated a bias towards fertilizer expenditure (Table 2). The mean value of the relative fertilizer expenditure of 7 subjects (9%) was significantly below 0.5, thus indicating a bias towards soil improvement. For 8 subjects (11%), $H_0$ could not be rejected indicating that they had no bias.

**Table 2.** *Distribution of subjects with biases. Each subject appears only once, in the category with the lowest applicable p-value.*

| Bias | p < 0.01 | p < 0.05 | p < 0.1 | Total |
|---|---|---|---|---|
| Bias towards fertilizer | 53 | 7 | 0 | 60 |
| Bias towards soil improvement | 6 | 1 | 0 | 7 |
| No bias | | | | 8 |
| **Totals** | | | | **75** |

## 3.2 Decision trajectories and benchmark

To analyze the variation in the subjects' biases more closely, we investigated the decision trajectories. Figure 3 shows the decision trajectories of all subjects within the 15 markets and the variation between the subjects' decision trajectories, and between the markets. Unlike other Cournot market-based studies that have analyzed subjects' rationality, we did not focus on theoretical equilibriums based on structural transparency, such as the Cournot Nash equilibrium or the competitive equilibrium. Instead, we calculated a near-optimal decision pattern using a Powell hill-climbing algorithm (Figure 3, top left corner). The resulting benchmark trajectory led to the highest accumulated production under the premise that all five subjects stuck to the same decision trajectory. Due to endogenous interactions, this benchmark did not represent a global optimum. However, it provided the means for comparing the empirical decision trajectories. The benchmark revealed that the highest accumulated production was achieved if a subject first chose a balanced expenditure strategy that slightly prioritized soil improvement to build up SOM stocks (R1 loop, Figure 1) and only in the last two rounds allocated the entire budget to fertilizer purchases in order to boost short-term production (R2 loop). Thus, theoretically, and from a rationality point of view, one could expect "end game behavior" to occur. However, we did not expect that to happen because we did not provide structural transparency, which is the basis for a fully rational decision-making. Figure 3 reveals that "end game behavior" was not an issue from a practical point of view.
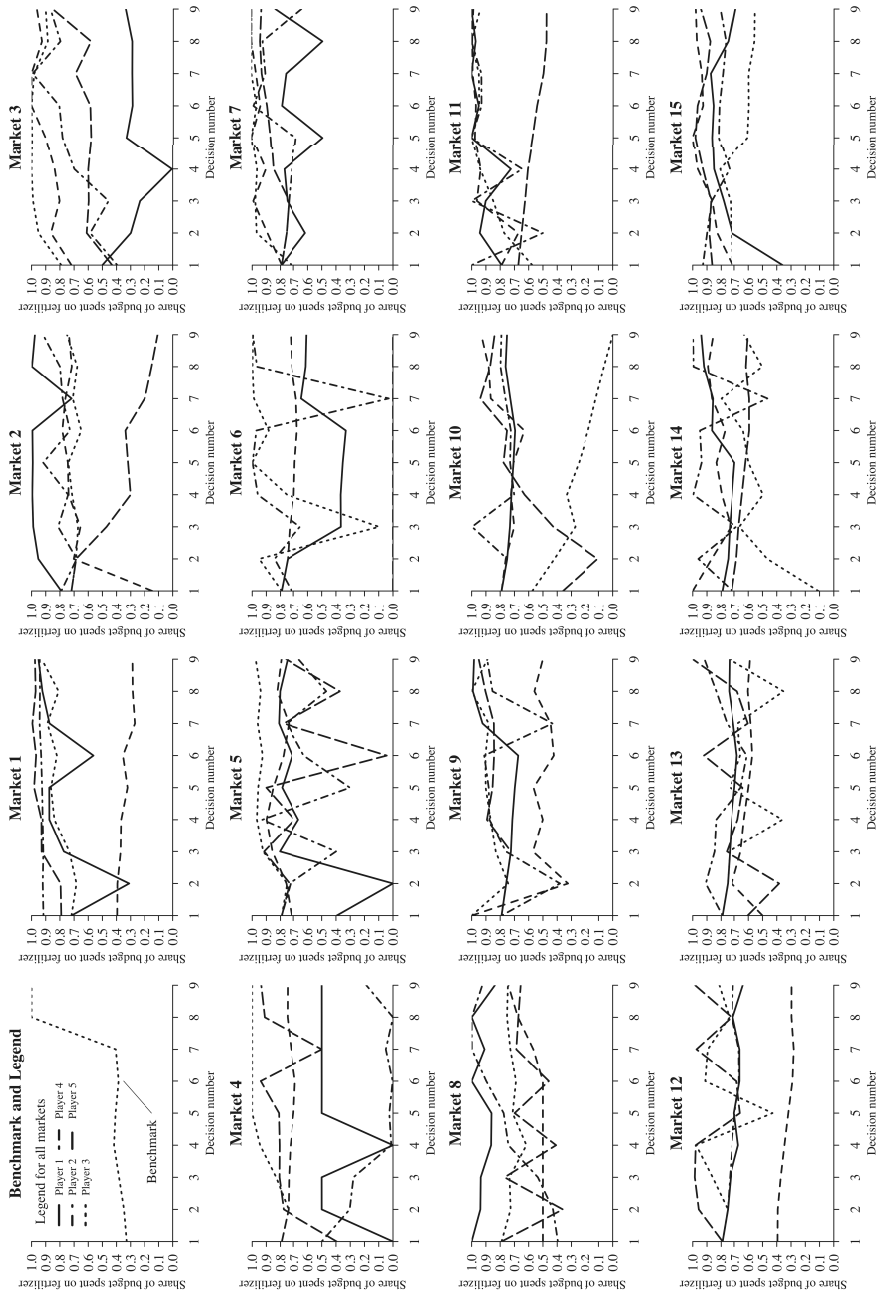
*Figure 3.* The subjects' decision patterns grouped according to the markets.
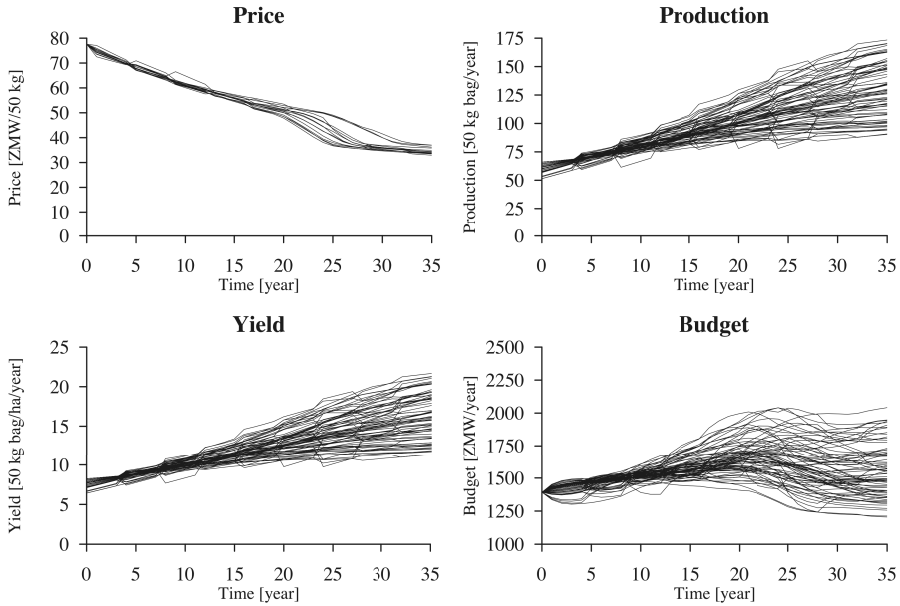
***Figure 4.*** *Trajectories of key variables in the experiment.*

The performance among subjects and markets varied. This variation did not only result from individual subject's decisions but also from the interaction between subjects within a market. Figure 4 shows that the model was parameterized such that yield and production followed an increasing trend and price drops throughout the experiment. All the subjects started with the same initial conditions with regard to budget, farm size and costs. However, for the duration of the experiment, the subject-specific variables production, yield, and budget showed increasing variation. Subjects who initially allocated a large share of their budget to soil improvement had smaller harvests (production) at the beginning of the experiment than subjects who allocated large shares of their budget to fertilizer purchases. This was because building up SOM is a slow process with a delayed effect on yields (R1 loop, Figure 1). In the model, once the SOM stock levels are built up, the R1 loop drives up yield and production. By contrast, subjects who focused on fertilizer purchases built up SOM levels mainly through the R3 loop, which was much less effective than R1. As a result, fertilizer-centered decisions resulted in lower production towards the end of the experiment. Decision trajectories that do not only focus on one of the two

alternatives and that even shift the focus throughout the experiment may lead to similar overall performance as calculated by Equation 7, despite distinctly different patterns.

## 3.3 Strategies

The subjects' biases towards certain expenditure categories in combination with the varying decision and performance patterns revealed in Figure 3 and Figure 4 led us to investigate the mechanisms linking decisions and performance further. In the first step, we analyzed the subjects' decisions to identify distinct decision strategies. A hierarchical cluster analysis using squared Euclidean distance as a clustering criterion was applied in order to group the decision trajectories based on relative fertilizer expenditure. The cluster analysis revealed 10 clusters that included between 2 and 16 subjects each (Figure 5).

In the second step of the analysis, we linked the clusters to performance. The performance of a subject was the result of endogenous interactions within markets, and therefore direct comparison between subjects in absolute terms—for example, of a subject's accumulated production (AP)—was limited. To analyze performance differences between the strategies, we complemented the absolute concept AP with the relative performance concepts "subject's rank within their market" (rank) and "subject's market share of accumulated production within the market" (relative accumulated production, rAP). Table 3 lists the significance levels of the two-tailed Mann-Whitney tests, which analyzed whether the means of subjects' rAP within one cluster differed from the means in other clusters. The analysis revealed that the majority of clusters differed significantly from each other in terms of performance. Clusters that did not reveal a significant difference in means either included a small number of subjects (n) or had similar performance outputs following different decision strategies. The latter can be explained by model dynamics that, in some cases, lead to similar performances, even when different strategies are applied. When we used the other performance indicators (rank and AP) for the analysis of means, we obtained very similar results to those presented in Table 3.
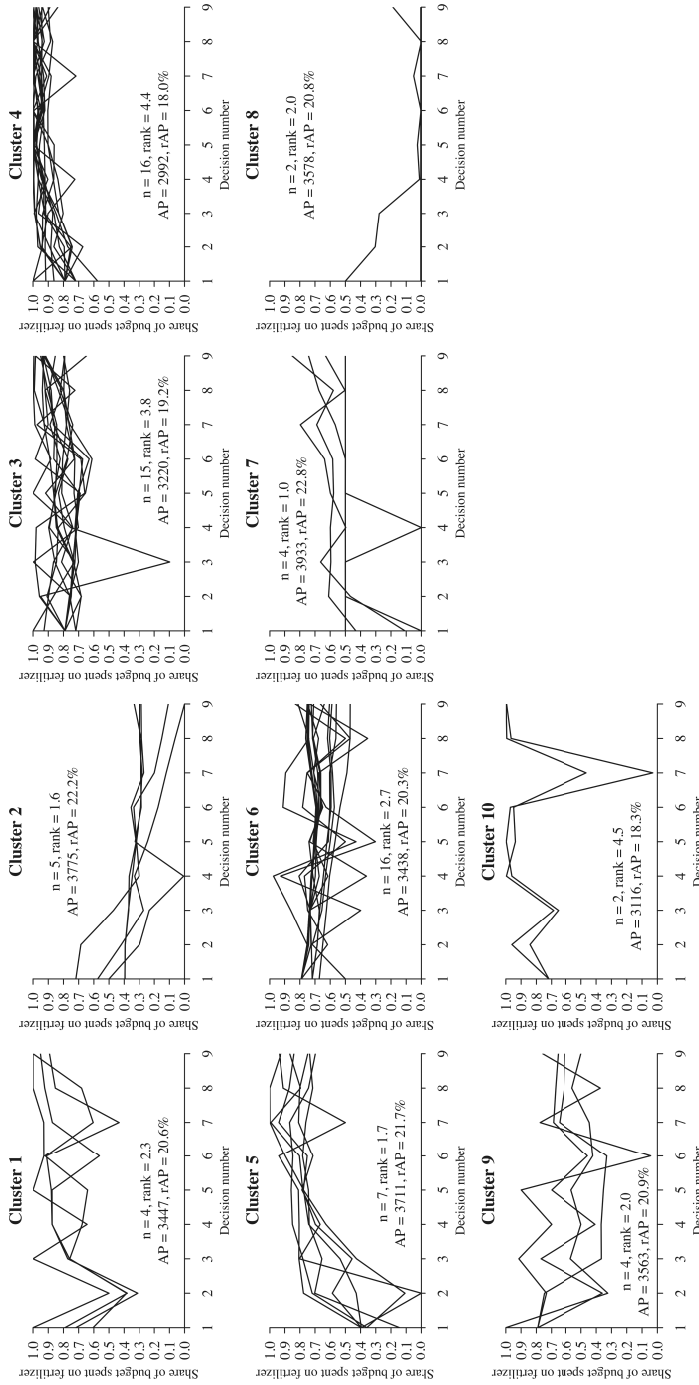
**Figure 5.** *Overview of the decision patterns and average values of performance indicators in the different clusters.*

*Notes: n – number of subjects included in the cluster; rank – average rank of the cluster's subjects in their respective market; AP – average accumulated production of the cluster's subjects in their respective market; rAP – average relative accumulated production (market share) of the cluster's subjects in their respective markets.*

**Table 3.** *Number and share of subjects in clusters, performance indicators and difference in means of relative accumulated production among clusters (C).*

| | $n^a$ | Share | $Rank^a$ | $AP^a$ | $rAP^a$ | Different means of rAP, Mann-Whitney test[b] | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | C1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| **C1** | 4 | (5%) | 2.3 | 3447 | 20.6% | | | | | | | | | |
| **C2** | 5 | (7%) | 1.6 | 3775 | 22.2% | - | | | | | | | | |
| **C3** | 15 | (20%) | 3.8 | 3220 | 19.2% | ** | *** | | | | | | | |
| **C4** | 16 | (21%) | 4.4 | 2992 | 18.0% | *** | *** | *** | | | | | | |
| **C5** | 7 | (9%) | 1.7 | 3711 | 21.7% | ** | - | *** | *** | | | | | |
| **C6** | 16 | (21%) | 2.7 | 3438 | 20.3% | - | ** | ** | *** | ** | | | | |
| **C7** | 4 | (5%) | 1.0 | 3933 | 22.8% | ** | - | *** | *** | - | *** | | | |
| **C8** | 2 | (3%) | 2.0 | 3578 | 20.8% | - | * | ** | ** | - | - | - | | |
| **C9** | 4 | (5%) | 2.0 | 3563 | 20.9% | - | - | ** | *** | - | - | ** | - | |
| **C10** | 2 | (3%) | 4.5 | 3116 | 18.3% | - | * | - | - | * | ** | - | - | - |

Notes:
[a] For explanation see Figure 5;
[b] significance levels: *** $p < 0.01$, two-tailed; ** $p < 0.05$, two-tailed; * $p < 0.1$, two-tailed.

The analysis of the number of subjects within the clusters revealed that successful clusters (rank ≤ 2; C2, C5, C7–9) included fewer subjects (n = 2–7, 22 subjects in total), who on average allocated 50% of their budget to fertilizer purchases. Clusters with an average rank higher than 2 (C1, C3, C4, C6, C10) included more subjects (n= 2–16, 53 subjects in total), who allocated on average 81% of their budget to fertilizer purchases. Thus, few subjects chose a successful long-term strategy (soil improvement) compared to many subjects who focused on a short-term oriented strategy (fertilizer purchase) that performed worse. The successful clusters all revealed strategies that put more weight on soil improvement than on fertilizer purchases at one point in time. In this way, the subjects built up their SOM stocks and performed well, even if they applied a fertilizer-centered strategy (e.g., towards the end of the experiment, as in the case of cluster 5). Subjects in the less successful clusters predominately focused on fertilizer expenditure and thus neglected to build up SOM levels.

## 3.4 Heuristics

Since the subject's choice of decision strategy would have performance implications, we investigated the decision rules within the different strategies (clusters) and formulated each cluster's specific heuristic. In this context, we use the term "heuristic" to describe a mathematical decision rule that was based on the information provided to the subjects prior to the decisions. A heuristic thus represents a rule of thumb to describe how subjects made their decisions. Research has shown that linear models of decision-making often provide good representations of underlying processes (Gary and Wood, 2011). In the absence of prior information about Zambian farmers' decision rules in the context of short-term and long-term production decisions, we applied a linear regression model to estimate the decision rule for each subject:

$$rEF_t = c_1 + a_1 P_{t-1} + a_2 Pr_{t-1} + a_3 y_{t-1} + a_4 B_{t-1} \qquad (9)$$

where $c_1$ is a subject-specific constant and $a_x$ is the subject-specific regression parameters. We included all information cues that were presented to the subjects on the record sheet prior to each decision (price, production, yield and budget; see Appendix B). For each subject, we conducted a linear regression and obtained the subject-specific intercept $c_1$ and information weights $a_x$ that specified the subject's heuristic according to Equation 9. The heuristics captured the majority of the variance in subjects' decisions with a mean R square value of 0.69.

Based on the subject-specific heuristics, we formed the aggregated heuristics of the different clusters. Accordingly, for each cluster, we calculated the strategy's specific heuristic by averaging the regression coefficient of its subjects. As a result, a cluster's heuristic was structured in the form of Equation 9, with parameter $c_1$ as the cluster's intercept and $a_x$ as the respective information weights (Table 4).

**Table 4.** *Heuristics identified in the clusters (C).*

| | Relative fertilizer expenditure heuristics[a] | | | | | n[b] | Rank[b] | AP[b] | rAP[b] |
|---|---|---|---|---|---|---|---|---|---|
| | Price | Production | Yield | Budget | Intercept | | | | |
| C1 | 0.0117 | 0.0507 | -0.2857 | -0.0008 | -0.0106 | 4 | 2.3 | 3447 | 20.6% |
| C2 | 0.0144 | 0.0041 | -0.0026 | -0.0001 | -0.6703 | 5 | 1.6 | 3775 | 22.2% |
| C3 | 0.0279 | 0.0291 | -0.0344 | -0.0008 | -1.6187 | 15 | 3.8 | 3220 | 19.2% |
| C4 | -0.0038 | 0.0017 | -0.0087 | 0.0003 | 0.6826 | 16 | 4.4 | 2992 | 18.0% |
| C5 | -0.0465 | -0.0353 | 0.0845 | 0.0013 | 3.5714 | 7 | 1.7 | 3711 | 21.7% |
| C6 | 0.0057 | 0.0046 | -0.0007 | -0.0006 | 0.9218 | 16 | 2.7 | 3438 | 20.3% |
| C7 | -0.0341 | -0.0056 | -0.0590 | -0.0003 | 3.8432 | 4 | 1.0 | 3933 | 22.8% |
| C8 | 0.0088 | 0.0056 | 0.0023 | -0.0013 | 1.0445 | 2 | 2.0 | 3578 | 20.8% |
| C9 | 0.0100 | 0.0199 | -0.1390 | -0.0009 | 1.0280 | 4 | 2.0 | 3563 | 20.9% |
| C10 | 0.0317 | 0.0466 | -0.1314 | -0.0015 | -1.2520 | 2 | 4.5 | 3116 | 18.3% |

Notes:
[a] Mean information weights for the decision heuristics;
[b] For explanation see Figure 5.

Our interpretation of the heuristic's coefficients was not trivial. Some of the clusters included only a small number of subjects and were therefore limited in terms of coefficient validity. In addition, the absolute comparability of clusters was limited because the strategies originated from market-specific, endogenous interactions among the subjects. Moreover, the different information cues had different numerical ranges. In our interpretation of Table 4, we therefore mainly focus on the overall results and the relative strength of information weights within information cues and the algebraic signs of information weights between information cues.

In Table 4, most of the budget information weights have a negative algebraic sign, which indicates that most decision strategies allocated smaller shares of the budgets to fertilizer purchases if the budgets increased (except for clusters 4 and 5). The information weights of price and production have the same algebraic sign (except for cluster 4), whereas the information weight of yield has the reverse algebraic sign (compared to price and production, except for cluster 7). The interpretation of the reverse algebraic signs of production and yield is difficult, because production is a linear function of yield with a positive multiplier (Equation 5). Explanatory

hypotheses can be derived from the subjects' remarks in the debriefing sessions. Some subjects indicated that, through the experiments, they had learned to differentiate between the two concepts "yield" and "production". Thus, if that was true for the majority of subjects, they might not have completely understood the positive correlation of the concepts and therefore they might have given reverse weights. Another point commonly made in the debriefing sessions was that the subjects had learned about the importance of dynamic bookkeeping. Thus, they many not have been used to applying dynamic heuristics based on farm-specific and market-specific information.

To investigate these hypotheses and to understand the heuristics better, we analyzed individual clusters. In the following, we highlight selected clusters that we found particularly interesting and that included more than 5 subjects—clusters 3–6. In clusters 3–6, cluster 4 performed worst on all performance indicators (rank, AP and rAP). Compared with the other three clusters, all information weights were relatively close to zero in cluster 4, which indicates that subjects within this cluster made decisions without giving much attention to the development of farm and market information. In addition, Figure 5 shows cluster 4 as strongly biased towards fertilizer purchases. Thus, cluster 4 followed a non-dynamic, a priori defined fertilizer strategy, which one of its subjects summarized by saying: "fertilizer works. We spent large shares of the budget to fertilizer purchases and didn't care about the other option." This supports the hypothesis above, that subjects in cluster 4 did not base their decisions on dynamic farm and market information.

Cluster 6 was similar to cluster 4, in that of no weight was assigned to farm and market information. However, Figure 5 shows that the subjects of cluster 6 applied a strategy of balanced expenditure with a moderate bias towards fertilizer purchases. This resulted in an average production that outperformed the low production of cluster 4. This finding also supports the hypothesis that farmers do not decide based on dynamic farm and market information. The subjects of cluster 6 expressed that they balanced their expenditures between the two production activities.

Of the remaining two clusters, one was among the most successful with regard to performance (cluster 5) and the other was among the least successful clusters (cluster 3). Both clusters gave relatively high weights to the provided farm and market information. However, the algebraic signs differed for all the weights. The successful subjects in cluster 5 started with comparatively low fertilizer expenditures, which means that they initially focused on the long-term strategy (soil improvement). Then, the subjects of cluster 5 decided adaptively, i.e., dynamically, based on the development of the information cues. By contrast, the subjects in cluster 3 started with relatively high fertilizer expenditures and increased the share of fertilizer expenditures even further, based on their dynamic decisions strategies. Thus, they even amplified their bias towards fertilizer expenditure. For both cluster 3 and cluster 5, which applied dynamic heuristics based on the provided farm and market information, we were not able to find explanations for the reverse algebraic sign of the information weights for yield and production, other than the hypothesis that the subjects might not have completely understood the positive correlation of the concepts. However, both clusters applied dynamic heuristics based on the provided farm and market information, but revealed highly significant differences in their performance indicators (Table 3).

## 3.5 Robustness of heuristics

The formation and analysis of the heuristics described above happened under the premise that the underlying data were the result of dynamic interactions among the subjects within the respective markets. Especially the heuristics of clusters with few subjects may have been biased due to the endogenous nature of the experiment. To test for robustness, we performed simulations with the heuristics presented in Table 4. Instead of the subjects making the decisions (as in the experiments), we implemented the heuristics into the simulation model and ran it for each cluster. By applying the same heuristic for all five farms, we tested how the heuristics worked in isolation. Figure 6 shows that the heuristics in Table 4 and their performance implications are robust to the experiments' endogenous interactions in most cases. In most of the

clusters, the simulated allocation decisions were very similar to the average decision trajectories from the experiments. Also, the simulated accumulated production per subject (APsim) was very close to the AP in most cases (the difference was less than 3%). Only clusters 5 and 7 revealed larger differences in decision trajectories and performance. While the simulated patterns of decision trajectories still showed an increasing trend (as the empirical trajectories), the increase was exaggerated in the simulation. This exaggerated the bias towards fertilizer and resulted in APsim 9% below AP in both cases. The exaggeration of the bias happened because the heuristics highly weighted price development. When the strategies used by subjects in clusters 5 and 7 were applied in combination with other strategies, they performed well (Table 4). However, their exclusive appearance in a market created endogenous interactions that led to a suboptimal output, because high production resulted in price decreases that triggered a shift towards a fertilizer-centered strategy. This indicates that, in some cases, the composition of strategies within a market matters for a strategy's performance.

To test the effect of strategy composition within a market, we conducted further simulations with combinations of selected heuristics. The results indicated that heuristics, which led to decision patterns similar to the subjects' empirical decision means shown in Figure 6, showed little variance in production, even with varying strategy compositions (e.g., heuristic 4 in Figure 7). However, the heuristics of clusters 5 and 7 that showed divergence from empiric pattern means in Figure 6, also revealed varying production patterns, depending on the strategy composition within the market (e.g., heuristic 5 in Figure 7). Thus, the performance of heuristics 5 and 7 was strongly influenced by endogenous interactions with other subjects, which was not the case for the other heuristics.
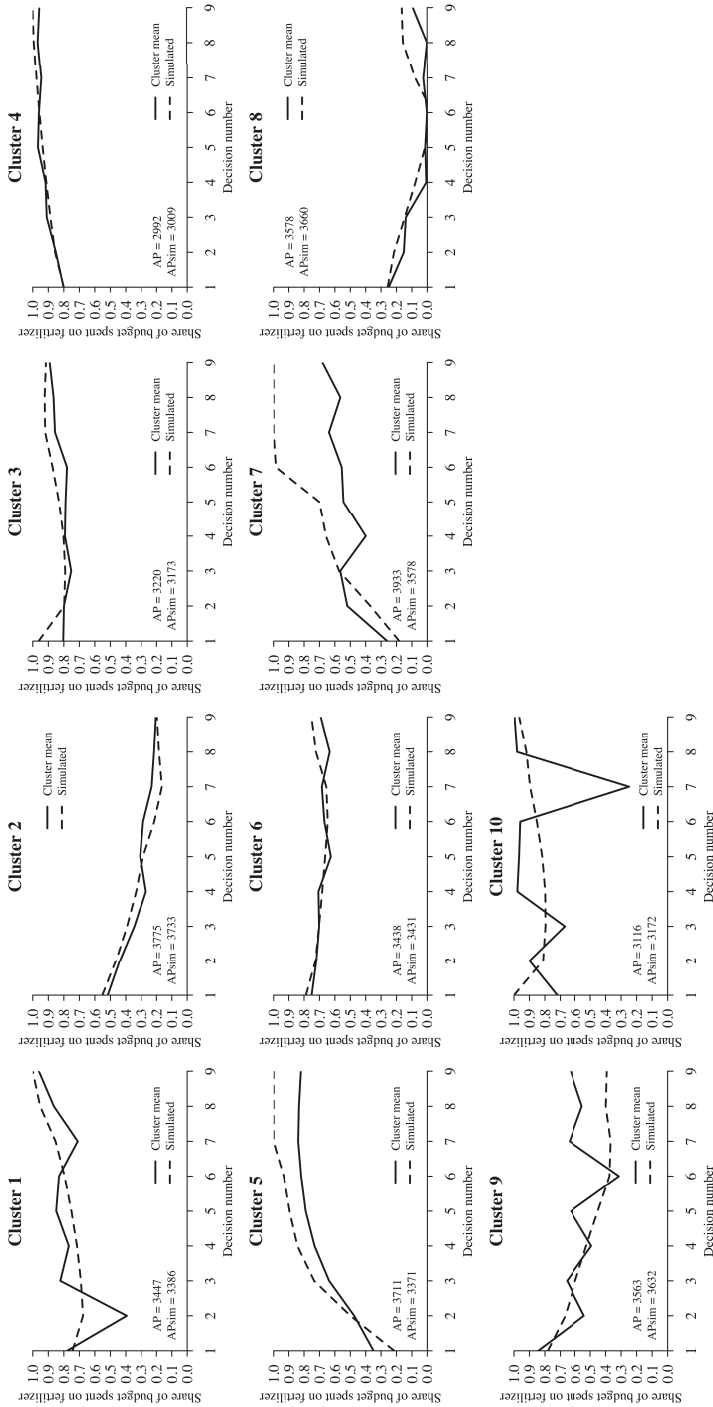
**Figure 6.** *Simulated heuristics versus the mean decisions per cluster.*

*Notes: AP – average accumulated production of the cluster's subjects in their respective market; APsim – average accumulated production of the cluster's subjects based on simulation.*
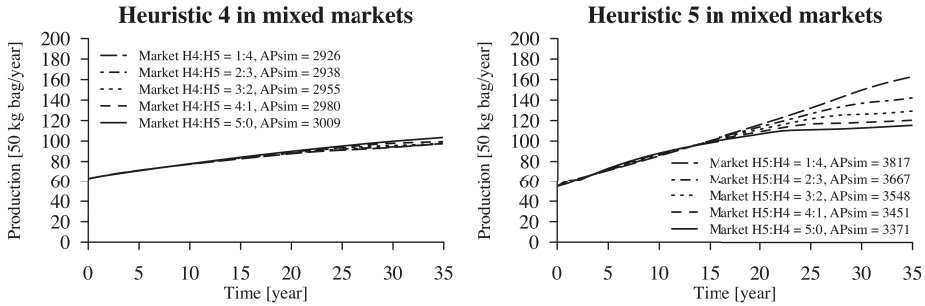
**Heuristic 4 in mixed markets**

Market H4:H5 = 1:4, APsim = 2926
Market H4:H5 = 2:3, APsim = 2938
Market H4:H5 = 3:2, APsim = 2955
Market H4:H5 = 4:1, APsim = 2980
Market H4:H5 = 5:0, APsim = 3009

**Heuristic 5 in mixed markets**

Market H5:H4 = 1:4, APsim = 3817
Market H5:H4 = 2:3, APsim = 3667
Market H5:H4 = 3:2, APsim = 3548
Market H5:H4 = 4:1, APsim = 3451
Market H5:H4 = 5:0, APsim = 3371

*Figure 7.* *Simulated production of heuristic 4 (H4) and heuristic 5 (H5) in varying combinations.*

*Note: APsim – average accumulated production of the cluster's subjects based on simulation.*

# 4. Discussion and conclusions

Smallholder farmers in sub-Saharan Africa repeatedly face situations of complex and dynamic budget allocation trade-offs between short-term and long-term production activities. Short-term activities, such as fertilizer application, help to cover immediate food needs, but they compromise future production. Long-term production activities, such as improving depleted soils, enhance future food production, but compromise current harvests. While regenerating depleted soils is an important leverage point for increasing long-term food availability, this is not a current practice. Increasing food demands will place pressure on food production systems, which will mean that soil regeneration will be unlikely to happen. We investigated Zambian smallholder farmers' decisions that governed long-term soil regeneration by using a semi-computerized, non-cooperative Cournot field experiment. In the experiment, the farmers (i.e., the subjects) aimed to maximize their maize production by repeatedly allocating a given budget to two maize production activities: fertilizer purchases (representing a short-term production strategy) and soil improvement (representing a long-term production strategy). Our results provided empirical evidence, based on the decisions of real farmers, that helped to understand the dynamic decision-making of

smallholder farmers in Zambia. In the following sections, we discuss our key findings, their implications, and the potential for further research.

## 4.1 Bias towards fertilizer use

The results showed that, overall, the subjects had a strong and significant bias towards decisions that were effective in the short-run but decreased food system outcomes and their resilience in the long-run (fertilizer purchase). While these findings are consistent with Donovan and Casey's (1998) hypothesis that smallholder farmers had high discount rates for benefits that would be realized far in the future, our results provided empirical evidence in support of this hypothesis. The findings have both theoretical and practical implications. First, the distinct bias towards short-term strategies could be an explanatory hypothesis for why long-term policies, such as the dissemination of conservation agriculture, are difficult to scale up (Giller *et al.*, 2009). Whereas short-term policies, such as fertilizer subsidy programs (FSPs), are in accordance with the farmers' mind-sets, long-term polices are not. Second, given the potential of long-term strategies to increase production, resilience, and sustainability, it would be crucial to scale up long-term strategies (Gerber, 2016; Stave and Kopainsky, 2015). Thus, to scale up long-term oriented strategies, a shift in farmers' decision-making is required, for example through agricultural extension (consultancy for farmers). However, it is not straightforward what the shift in mind-set should include and how it could be achieved. The following findings may help in this respect.

## 4.2 Variation in decision strategies

Besides the clear overall bias towards short-term production activities, we found great variability in the farmers' decision patterns. A non-negligible number of subjects either clearly prioritized the regeneration of soil organic matter (SOM) over short-term benefits or had no bias towards one of the expenditure categories. To analyze this variation, we structured the decision patterns into 10 clusters, each of which represented a distinct decision strategy. The number of subjects within the clusters

varied. Especially the clusters that performed best in terms of production comprised a small number of subjects and at least at one point during the experiment focused on improving soil fertility. Clusters that performed worse included the majority of subjects and were centered on fertilizer purchases.

## 4.3 Decision dynamics and success factors

To investigate the link between decisions and performance further, we developed heuristics for each cluster in the form of mathematical decision rules based on the information cues that were provided to the subjects prior to them making their decisions. The analysis of the clusters' heuristics revealed that some heuristics that covered the majority of subjects were rather insensitive to the provided farm and market information and thus did not take into account the dynamics of the food production system. The performance of those "non-dynamic heuristics" varied and depended on a priori decision rules, which we were not able to detect due to the study design. The closer the non-dynamic heuristics were to the decision benchmark (Figure 3), the better the heuristics performed. However, some subjects reacted to the provided information and made their decisions in response to the dynamic context. The performance of such "dynamic heuristics" also varied. Heuristics that started with low fertilizer expenditures and dynamically shifted in their focus towards higher fertilizer expenditure were most successful in terms of production. Dynamic heuristics that started and remained with high fertilizer expenditure shares were less successful in terms of production. Heuristics that started with high shares of fertilizer expenditure but showed a decreasing trend over the experiment's duration led to a medium performance because the SOM stocks were built up too late to have an impact in the experiment. Thus, we found both, dynamic and non-dynamic heuristics, and both groups had varying performances.

Deciding dynamically alone does not guarantee success. Instead, we found two preconditions or drivers of success for dynamic heuristics that resulted in above-average performance in terms of production. First, the most successful subjects initially focused on replenishing SOM stocks before reaping the short-term benefits

from the application of inorganic fertilizer. This criterion was necessary to trigger the food production system's long-term leverage point. Second, successful subjects dynamically adjusted their decisions based on farm and economic information. This criterion was necessary but not sufficient to achieve a good performance. Subjects who adjusted their decisions dynamically did not perform better than other subjects, unless they prioritized soil organic matter replenishment at the outset. Thus, dynamic adjustment is only beneficial if the first condition is met.

## 4.4 Dynamic interaction of decision strategies

We further analyzed how the heuristics performed in terms of production if they were part of markets with varying combinations of different heuristics. Most of the heuristics revealed stable production patterns, even when the composition of heuristics within the market varied. Thus, the majority of the heuristics were robust to the endogenous interactions between different decision strategies within the markets. However, we found that two heuristics reacted strongly to market signs (prices) and that were sensitive to the interactions between decision strategies. The production pattern of those two heuristics largely depended on the other decision strategies that were present in the market. For example, accumulated production was rather low when all five farms applied the same heuristic. However, if these heuristics were part of markets that embraced a mix of decision strategies, they had the potential to lead to top performances in terms of production. This indicates that the performance of heuristics that place a strong emphasis on price information will be strongly influenced by dynamic and endogenous interactions within the respective markets.

## 4.5 Practical implications

Overall, a shift in mind-set towards favoring long-term production activities is needed to increase sub-Saharan Africa's food production sustainably. Our findings revealed relevant information for agricultural extension, which in practice may facilitate such a shift. The observed variation in decision strategies means that there may not be a single solution for all cases. Instead, agricultural extension should design

interventions with the potential and flexibility to take into account diverse decision strategies within a group of farmers. In that way, agricultural extension could build on current practices instead of introducing radical paradigms or, in some cases, completely new ones.

The two drivers of success have further implications for practice. The first driver of success—initially prioritizing the replenishment of SOM stocks—takes considerable time to increase production substantially. This creates a severe conflict with the need to secure short-term benefits (immediate food needs) through the use of inorganic fertilizer. Thus, an important prerequisite for implementing a strategy designed to replenish SOM might be to explicitly combine it with the application of inorganic fertilizer in order to reduce the trade-off between short-term and long-term objectives (Kearney *et al.*, 2012).

Concerning the second driver of success, the dynamic adjustment of decisions, our data show that it is quite uncommon for farmers to adjust their decisions dynamically to economic information, such as prices. However, Spicer reports that in-depth interviews with smallholder farmers in Zambia revealed that they were very capable of adjusting their decisions dynamically in other domains (Spicer, 2015). For example, farmers used agronomic information that enabled them to decide about biological production aspects, such as crop rotation. The implementation of the second driver of success can thus build on what farmers already do, which is to adjust their decisions dynamically based on agronomic information, and use this for comparison when making decisions that need to include economic information.

Another challenge for implementing the second driver of success arises from the endogenous interactions between decision strategies within a market. Our analysis revealed that the performance of some dynamic heuristics was dependent on the composition of the heuristics within the markets. Such interaction-sensitive heuristics may be attractive to individual farmers because they are successful in terms of production if other farmers choose other, less successful strategies. However, from a broader perspective, dynamic heuristics that are sensitive to endogenous interaction

bear the risk of performing below their potential. Thus, alternative heuristics that have a slightly lower maximal production potential but react less sensitively to endogenous interactions might be preferable. These insights further highlight the need for context-specific extension services, and in general it should be emphasized that there is no universal optimal way for smallholder farmers to make and dynamically adjust decisions. This reinforces the need for building adaptive capacity rather than promoting the broadest possible diffusion of technical training.

## 4.6  Further research

Findings from experimental studies are not conclusive in the sense that they originate from a laboratory environment and not from a real-world context. The external validity of experiment-based findings is thus a common concern and ultimately needs empirical confirmation based on real world data. However, previous research has shown that the external validity of experimental findings allows for some generalization (e.g., Anderson *et al.*, 1999) and we believe that our experimental setup, which was as close as possible to the subjects' situation on their respective farms contributed to the potential for external validity of our findings. In particular, the use of a complex model that included time delays and feedback processes, and that was calibrated using data from Zambia, allowed us to mimic farmers' real-world decision tradeoffs. The external validity of our findings is further supported by the field experiment setting, in which real farmers were subjects (Lara-Arango *et al.*, 2017).

Although we have revealed insights into the dynamic decision-making of sub-Saharan Africa's smallholder farmers in the context of short-term and long-term production activities with conflicting objectives, there are several ways in which our findings could be expanded and complemented. We found that some of the subjects decided on a priori heuristics that we could not explain with our study design. However, to develop agricultural extension towards long-term production activities, knowledge of the foundation of a priori heuristics might be useful. Our study design could be enriched by individual, semi-structured interviews with all subjects after the

completion of the experiment. Such interviews would allow qualitative information about the a priori heuristics to be gathered, but might also be a means to explore why even dynamic heuristics reveal reverse algebraic signs for the information weights of yield and production.

Further research should address the process of decision-making. Our subjects consisted of couples and single players, and exploratory analysis of our data revealed that neither their performance nor their decision about strategy was affected by these facts. However, couples mentioned in the debriefing sessions that they were not used to decide together. Thus, investigating on-farm decision processes with regard to performance might both inform agricultural extension about key decision persons and be useful for evaluating the external validity of the findings. In sum, our results provide important evidence of dynamic decision-making by farmers to enhance food availability sustainably in sub-Saharan Africa and serve as a steppingstone for further research in this field.

## Acknowledgements

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# Appendixes

## Appendix A: Data Gathering Protocol

1. Gather the participants (5 couples, that in real life each actually run a farm together).

2. Introduction and Instructions: Hello and welcome everybody.

*Introduction of all that are present*

A. Purpose

Thank you for being here. Today we gather information for learning how you make different decisions. Andreas is doing a schoolwork study for his PhD in collaboration with Dr. Nyanga at UNZA[6]. He is interested in learning how you make decisions as couples. The information will be used for academic purposes and may be published in academic journals. Is that clear and ok for you?

B. Roles

We would like to gather the information through playing a game together. The roles are: I am the moderator, who will interact with you. Andreas is the computer man, who will be putting the information in the computer and giving the results. Cain and Eukeria will help me moderating the process, transmitting information between you and the computer man. You, the couples, are the players who make decisions.

C. Game

Every couple will manage a farm. You all have a common main goal for your farm. In this game the main goal is to maximize your accumulated maize production over the whole game. To reach the goal of maximize your production, you must decide how much money (Kwachas) you want to spend on two options. The first option is buying own fertilizer (not through government or NGO subsidies). And the second option is spending financial means to improve your soil through crop residue retention and manure application. In this game we just have these two options and we

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[6] University of Zambia

are not considering other options such as lime application, crop rotation, Musangu tree plantation, etc.

Here is some information to understand your farm: Each couple cultivates 8 limas (equivalent to 2 hectares) of maize on its farm, so your decisions are limited to this area. The maize yield level is currently around 7 bags of 50kg per lima; the current/starting production therefore is around 60 bags of 50kg per farming season. The current/starting producer price of maize at your market is around 75 Kwacha per 50kg bag.

In the beginning your budget for the two options is 1392 Kwacha. In the first option, which is buying fertilizer, a 50 kg bag of fertilizer cost 550 Kwacha. In the second option, which is crop residue retention and manure application, a lima costs you 117 Kwacha, adding external organic matter becomes more expensive.

For you to make decisions, the moderator will come to you and give you information about your budget, yield, current production and market price. You will then decide how much of the budget you want to spend on fertilizer and how much you want to spend to improve your soils. The moderator will take note of your decision and bring it to Andreas. He will put your decision into the computer and calculate the new budget, yield, production and price. The moderator will bring this new information back to you so that you can again decide how much money you will spend for fertilizers and soil improvement. We will have 9 rounds in this game. Thus, these dynamics will continue until we complete 9 periods (you make 9 decisions). The game will be completed in 1-2 hours approximately.

At the end of the game, the computer calculates your total production for the entire game and you will be rewarded with a present depending on your results. We brought a couple of items of which the best performing couple can choose one item first, the second best performing couple second, etc.

*Show the goods (2kg sugar, 1kg sugar, 750ml oil, big laundry soap, small laundry soap)*

If you have difficulties to make your decision, think of how you decide on your own, real farm and always keep in mind that your goal is to maximize your production!

We will have the possibility to clarify procedural questions during the game, but not ask for help in decision making. So far, is the game clear to you? Are you willing to participate? If you do not want to participate or feel uncomfortable, you can withdraw.

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Remarks to the instructor:

It is ok to clarify procedural questions: e.g., what happens after we make a decision? Do we have to spend the entire budget to these two policies? Etc.

It is also ok to clarify the meaning of words (e.g., yield)

Do not give clues that may directly influence the decision making process. E.g., do not answer questions regarding what should be done such as "should I allocate more on fertilizers?" or "How can I make the highest production in the game?"

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3. Split the participants up.

In this game it is the idea that you keep your decisions and results as a secret within your farm and do not share them with the other couples. So please, keep communication between the farms at a low level. However, once the game is finished and we have all the results from everyone, you are very free to share experiences and strategies with each other!

Give your best and good luck!!

4. Start the actual rounds.

After first round: explain that yield, production, price and budget changes. Costs stay the same.

5. Save the rounds.

*Take a copy (soft or hard) from the interaction sheets and save it.*
*Give a hard copy to the farmers as a feedback.*

6. Conclude with an aftermath session.

At this point the game is over and you are free to leave if you wish. However, if you appreciate, we will have a feedback session explaining some ideas of the game.

## Appendix B: Record Sheet

Farm Number:_____     Data Collection Set-Nr:___

Name of Participants:

_____

_____

Input prices:
- 50 kg Fertilizer costs 550 ZMW
- 1 lima improved soil costs 117 ZMW, for further improvement the price increases

| Round | | | | Budget | Soil | **Fertilizer** |
|---|---|---|---|---|---|---|
| 0 | Yield ≈7 bags/lima | Production ≈60 bags | Price ≈75 ZMK/bag | 1392 ZMW | | |
| 1 | Price | Yield | Production | Budget | **Soil** | Fertilizer |
| 2 | Production | Price | Yield | Budget | Soil | **Fertilizer** |
| 3 | Yield | Production | Price | Budget | **Soil** | Fertilizer |
| 4 | Price | Yield | Production | Budget | Soil | **Fertilizer** |
| 5 | Production | Price | Yield | Budget | **Soil** | Fertilizer |
| 6 | Yield | Production | Price | Budget | Soil | **Fertilizer** |
| 7 | Price | Yield | Production | Budget | **Soil** | Fertilizer |
| 8 | Production | Price | Yield | Budget | Soil | **Fertilizer** |
| 9 | Yield | Production | Price | Budget | **Total Production** | |

Date: _____     Place: _____