HOUSEHOLD STRUCTURE AND LABOR ALLOCATION: THE CASE OF RISK INSURANCE IN MALI AND TECHNOLOGY ADOPTION IN BURKINA FASO

By

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ABSTRACT

HOUSEHOLD STRUCTURE AND LABOR ALLOCATION: THE CASE OF RISK INSURANCE IN MALI AND TECHNOLOGY ADOPTION IN BURKINA FASO

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The low level of adoption of labor-saving technologies makes human labor a central productive factor among small-scale farmers in sub-Saharan Africa. Yet, many of these farmers face missing labor markets such that household composition becomes an important source of labor endowment. This dissertation investigates family structure and labor allocation using detailed household agricultural production data under two different contexts: (i) when households are subject to production risk and (ii) in the wake of the introduction of a new agricultural technology.

The first study uses a two-wave plot level dataset collected in 2009 and 2012 and applies multiple levels of fixed effect and alternative functional forms to investigate labor allocation across collective plots –collectively owned by extended family members and managed by the heads of extended family household– and individual plots managed by the other adult male members. The empirical findings provide strong evidence that collective plots receive much more labor and achieve higher crop yield per hectare relative to individual plots.

These findings, which are unanticipated with respect to what the theory on collective production predicts, are rationalized by the claim that collective plots serve as a mechanism for an ex-ante risk mitigation strategy against production uncertainty. Such a claim is tested using the historical coefficient of variation of rainfall to show that households living in villages with higher rainfall variability present a significantly higher labor allocation gap in favor of their collective plots relative to individual plots. Furthermore, household level data analysis indicates that nuclear households in places with higher historical rainfall variability are more likely to be engaged in collective farming.

The second study uses randomized control trial (RCT) data combined with the difference-in-difference estimation method to investigate household labor response to the introduction of the

microdosing technology (a fertilizer application technique) among extended family households –formed by multiple nuclear households– and purely nuclear family households in Burkina Faso. The findings indicate that the intervention significantly increased labor allocation among nuclear households, which is as expected, given that the microdosing technology is very labor-intensive. In contrast, we find that the program significantly reduced labor allocation among extended households. Two explanations are provided for this differential impact according to family structure.

The first relates to differences in control over productive resources across the two types of households. Specifically, within the extended households, labor is shared across the collective and individual plots. This labor arrangement is likely to constrain the amount of labor that can be allocated to the plots receiving the microdosing technology. The second explanation is related to differences in incentives. Nuclear households are sole claimants of any incremental output, which may give them greater incentive to exert more effort to meet the labor requirement of the microdosing technology. In contrast, extended family household members are rewarded based on their need rather than their efforts, providing them less incentive relative to those in purely nuclear family households.

While the findings from the two studies seem at first glance contrasting, a close consideration of the settings of the two studies shows that these findings are specific to their context. This calls attention to how factors governing productive resource allocations among households with missing and incomplete markets are numerous, multifaceted, and context-specific to the household structure. This highlights the need for more microeconomic household analysis for better targeting aiming at increasing agricultural productivity, and consequently, food security.

This dissertation is dedicated to my late brother, Saidou Ouedraogo

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KEY TO ABBREVIATIONS

AGRODIA	Association des Grossistes et Détaillants d’Intrants Agricoles
CFA	Communauté Financière Africaine
CV	Coefficient of variation
DID	Difference-in-difference
FAO	Food and Agriculture Organization
FCFA	Francs Communauté Financière Africaine.
FE	Fixed effects
Ha	Hectare
HH	Households
HHCYFE	Household-crop-year fixed effect
ICRISAT	International Crops Research Institute for the Semi-Arid Tropics
INERA	Institut de l'Environnement et de Recherches Agricoles
IPA	Innovations for Poverty Action
ITT	Intend to treat
Kg	Kilograms
PMYFE	plot-manager-year fixed effects
RCT	Randomized control trial
SD	Standard Deviation
SfC	Saving for Change
USAID	United States Agency for International Development

INTRODUCTION

Motivation

Most of the world's food insecure live in Sub-Saharan Africa (SSA) where more than a quarter of the population is

undernourished (FAO, 2014). A high proportion of these people rely on subsistence farming as their main source of livelihood. At the same time, agricultural production in the region is plagued by low productivity due to multiple factors including low and decreasing soil fertility (Drechsel et al., 2001; Nachtergaele, F. O. et al., 2011; Jones et al., 2013; Josephson et al., 2014) combined with low agricultural technology adoption rates, and limited access to productive resources, such as labor (Croppenstedt and Goldstein, 2013; Moser and Barrett, 2003; Lee et al., 2006; Barrett et al., 2008; Smale et al., 2013), *inter alia.*

Access to labor has important implications for agricultural productivity among households in this region, especially in West Africa, where a substantial empirical literature finds that differences in labor access are strongly reflected in crop yield performance (Udry, 1996; Goldstein and Udry, 2008; Kazianga and Wahhaj, 2013; Guirkinger et al., 2015; Guirkinger and Platteau, 2017). These finding mostly stem from the fact that labor is an important productive factor for households in this region, especially among small-scale subsistence farmers. This is not only because it compensates for the lack of agricultural technology adoption (de Ridder et al., 2004; West, 2010), but also because most agricultural technologies available in this region are labor intensive (Moser and Barrett, 2003; Barrett et al., 2004, Kijima et al., 2011). Trends in agricultural technology adoption show that an overwhelmingly high proportion of subsistence farmers still heavily rely on hand tools in SSA, due to a decreasing trend in agricultural mechanization (Ashburner and Kienzle; 2011; Baudron et at., 2015; Sheahan and Barrett, 2014). This makes the availability of human power crucial for successful agricultural intensification.

Despite the central role of human labor in agricultural production among small-scale subsistence households, they usually face missing or incomplete labor markets and must rely on family members to satisfy their labor needs. In this context, household composition becomes an important source of labor endowment. This makes an understanding of the relationship between household structure and labor allocation decision-making relevant for achieving successful implementation of agricultural development programs.

However, accurately identifying such factors is challenging, especially among rural subsistence households in SSA, where factors governing the allocation of productive resources are numerous, multifaceted, and often context-specific to the household structure (Kazianga and Wahhaj, 2017; Theriault et al., 2017). This underscores the need for further research related to household structure and productive factor allocation. This has motivated the current dissertation on linkages between household structure and labor allocation under distinct production organizations in Burkina Faso and Mali.

Research contribution

The dissertation is organized in two parts. In the first part, I investigate how labor allocation varies across plots within the same household, depending on plot management structure– that is, plots that are collectively owned by all extended family members in the households or individual plots owned by nuclear family households. This part of the dissertation contributes to the literature in several ways. First, to my knowledge, no other study applies plot-manager-year fixed effects to investigate labor allocation among extended households, where the same plot manager simultaneously manages collective plots and his own individual plots. Such an approach provides a powerful way to establish that any differences observed in labor allocation across the collective and individual plots can be solely attributed to the role that collective plots play within the household, rather than the characteristics of the individual who manages them.

Second, the study sheds light on a scantily understood subject, which is the role of collective farming as an ex-ante production risk mitigation strategy. To capture historical exposure to production uncertainty, I follow the approach of Dillon et al. (2011) by computing the historical coefficient of variation of rainfall over a period of twenty-seven years (1981-2007). I then use this coefficient of variation to test my claim about collective farming being an ex-ante risk mitigation strategy. Specifically, I investigate differences in labor allocation across collective and individual plots among extended family households across villages with different levels of rainfall variability.

The notion that collective farming can be favored when production uncertainty prevails has been mentioned in the theoretical literature (Putterman, 1983; Carter, 1987; Deininger, 1995; West, 2010) but with very limited empirical evidence. Among the few studies is the paper by Rosenzweig and Wolpin (1985), where the authors exploit weather variability to investigate variation in household-level farm profits by family structure in India. To my knowledge, the current study is the first to use detailed plot-level data, combined with historical rainfall variability, to empirically investigate collective farming among extended family household members as an ex-ante risk mitigation strategy.

The second part of the dissertation examines how nuclear and extended family households allocate labor differently in response to the introduction of a new agricultural technology in Burkina Faso.[1] The technology in question is microdosing, which is a specific fertilization technique. The technology presents important distinctive features. It has the potential to significantly increase crop yield and requires much less fertilizer, making it less financially constraining and more environmentally friendly relative to the broadcasting technique (ICRISAT; 2012; Resnick et al., 2012). These features lead some analysts to perceive this technology as a promising way to achieve sustainable agricultural intensification (Juma et al., 2013, Aune and Coulibaly, 2015). However, it is very labor-intensive, especially at the time of fertilizer application and planting. The benefits of microdosing on one hand, and its intensive labor requirement on the other hand, make it an ideal subject to examine labor responses to its introduction.

The study uses data from a randomized control trial (RCT) in which the microdosing technology is exogenously introduced to the targeted households. The exogenous variation in the availability of the technology provides a strong way to establish the direction of causality of the differential impact of the

[1] This study is co-authored by Andrew Dillon and Maria Porter.

technology based on household structure. Moreover, to increase precision in our estimates, we combine the RCT data with the difference-in-difference estimation method. To our knowledge, the current work is the first to apply this approach to investigate the potential household structure differential effects of a new agricultural technology on labor allocation.

REFERENCES

REFERENCES

Ashburner, J. E., & Kienzle, J. (2011). Investment in agricultural mechanization in Africa: Conclusions and recommendations of a round table meeting of experts (3-5 June 2009. Arusha, Tanzania). FAO, Roma (Italia).

Aune, J.B. and Coulibaly, A. (2015). Microdosing of Mineral Fertilizer and Conservation Agriculture for Sustainable Agricultural Intensification in Sub-Saharan Africa. In Sustainable Intensification to Advance Food Security and Enhance Climate Resilience in Africa (pp. 223-234). Springer International Publishing.

Barrett, C. B., Moser, C. M., McHugh, O. V., & Barison, J. (2004). Better technology, better plots, or better farmers? Identifying changes in productivity and risk among Malagasy rice farmers. American Journal of Agricultural Economics, 86(4), 869-888.

Barrett, C. B., Sherlund, S. M., & Adesina, A. A. (2008). Shadow wages, allocative inefficiency, and labor supply in smallholder agriculture. Agricultural Economics, 38(1), 21-34.

Baudron, F., Sims, B., Justice, S., Kahan, D. G., Rose, R., Mkomwa, S., & Gérard, B. (2015). Re-examining appropriate mechanization in Eastern and Southern Africa: two-wheel tractors, conservation agriculture, and private sector involvement. Food Security, 7(4), 889-904.

Carter, M. R. (1987). Risk sharing and incentives in the decollectivization of agriculture. Oxford Economic Papers, 39(3), 577-595.

Clarke, L., & Bishop, C. (2002). Farm power-present and future availability in developing countries. Agricultural Engineering International: CIGR Journal.

Croppenstedt, A., Goldstein, M., & Rosas, N. (2013). Gender and agriculture: inefficiencies, segregation, and low productivity traps. *The World Bank Research Observer*, *28*(1), 79-109.

de Ridder, N., Breman, H., van Keulen, H., & Stomph, T. J. (2004). Revisiting a ‘cure against land hunger’: soil fertility management and farming systems dynamics in the West African Sahel. Agricultural Systems, 80(2), 109-131.

Deininger, K. (1995). Collective agricultural production: A solution for transition economies? World Development, 23(8), 1317-1334.

Dillon, A., Mueller, V., & Salau, S. (2011). Migratory responses to agricultural risk in northern Nigeria. American Journal of Agricultural Economics, 93(4), 1048-1061.

Drechsel, P., Gyiele, L., Kunze, D., & Cofie, O. (2001). Population density, soil nutrient depletion, and economic growth in sub-Saharan Africa. Ecological Economics, 38(2), 251-258.

FAO, IFAD. "WFP (2014) The state of food insecurity in the world 2014: strengthening the enabling environment for food security and nutrition." FAO, Rome.Goldstein, M., & Udry, C. (2008). The profits of power: Land rights and agricultural investment in Ghana. Journal of Political Economy, 116(6), 981-1022.

Gollin, D., & Rogerson, R. (2014). Productivity, transport costs and subsistence agriculture. Journal of Development Economics, 107, 38-48.

Guirkinger, C., Platteau, J. P., & Goetghebuer, T. (2015). Productive inefficiency in extended agricultural households: Evidence from Mali. Journal of Development Economics, 116, 17-27.

Guirkinger, C., & Platteau, J. P. (2017). Transformation of African Farm Households: A Short Survey of Economic Contributions. Journal of Demographic Economics, 83(1), 41-50.

ICRISAT. 2012. Fertilizer Microdosing, July 2012.

Jones, A., Breuning-Madsen, H., Brossard, M., Dampha, A., Deckers, J., Dewitte, O., & Le Roux, P. (2013). Soil atlas of Africa.

Josephson, A. L., Ricker-Gilbert, J., & Florax, R. J. (2014). How does population density influence agricultural intensification and productivity? Evidence from Ethiopia. Food Policy, 48, 142-152.

Juma, C., Tabo, R., Wilson, K., & Conway, G. (2013). Innovation for sustainable Intensification in Africa. London: The Montpellier Panel, Agriculture for Impact.Kazianga, H., & Wahhaj, Z. (2013). Gender, Social Norms, and Household Production in Burkina Faso. Economic Development and Cultural Change, 61(3), 539-576.

Kazianga, H., & Wahhaj, Z. (2017). Intra-household resource allocation and familial ties. Journal of Development Economics, 127, 109-132.

Kijima, Y., Otsuka, K. and Sserunkuuma, D. (2011). An inquiry into constraints on a green revolution in Sub-Saharan Africa: the case of NERICA rice in Uganda. World Development, 39(1), 77-86.

Lee, D. R., Barrett, C. B., & McPeak, J. G. (2006). Policy, technology, and management strategies for achieving sustainable agricultural intensification. Agricultural economics, 34(2), 123-127.

Moser, C. M., & Barrett, C. B. (2003). The disappointing adoption dynamics of a yield-increasing, low external-input technology: the case of SRI in Madagascar. Agricultural Systems, 76(3), 1085-1100.

Nachtergaele, F. O., Petri, M., Biancalani, R., Van Lynden, G., Van Velthuizen, H., & Bloise, M. (2011). An Information database for land degradation assessment at global level. Global land degradation information system (GLADIS).

Putterman, L. (1983). A modified collective agriculture in rural growth-with-equity: Reconsidering the private, unimodal solution. World Development, 11(2), 77-100.

Resnick, D., Tarp, F., & Thurlow, J. (2012). The political economy of green growth: Illustrations from Southern Africa (No. 2012/11). WIDER Working Paper.Rosenzweig, M. R., & Wolpin, K. I. (1985). Specific experience, household structure, and intergenerational transfers: farm family land and labor arrangements in developing countries. The Quarterly Journal of Economics, 961-987.

Sheahan, M., & Barrett, C. B. (2014). Understanding the agricultural input landscape in sub-Saharan Africa: Recent plot, household, and community-level evidence.

Smale, M., Byerlee, D., & Jayne, T. (2013). Maize revolutions in sub-Saharan Africa. In an African green revolution (pp. 165-195). Springer Netherlands.

Theriault, V., Smale, M., & Haider, H. (2017). How Does Gender Affect Sustainable Intensification of Cereal Production in the West African Sahel? Evidence from Burkina Faso. World Development, 92, 177-191.

Udry, C. 1996. “Gender, Agricultural Production, and the Theory of the Household.” Journal of Political Economy, 104(5), 1010-1046.

West, C. T. (2010). Household Extension and Fragmentation: Investigating the Socio-Environmental Dynamics of Mossi Domestic Transitions. Human Ecology 38.3, pp.363-376.

1 INTRA-HOUSEHOLD LABOR ALLOCATION AND EVIDENCE OF RISK INSURANCE AMONG EXTENDED FAMILY MEMBERS IN MALI

1.1 Introduction

Labor plays a crucial role in agriculture among many farmers in Sub-Saharan Africa due to limited access to labor-saving technologies. Its availability for crop cultivation is important such that plot-level crop yield performance is contingent on how much labor is allocated to the plot. Indeed, numerous studies on households in West Africa find differences in crop yield across plots with similar characteristics within the same household due to differences in labor allocation across these plots (Udry, 1996; Kazianga and Wahhaj, 2013; Guirkinger and Platteau, 2014; Guirkinger et al., 2015; Kazianga and Wahhaj, 2017; Guirkinger and Platteau, 2017; Theriault et al., 2017). Given that labor remains a central productive resource among these farmers (Moser and Barrett, 2003; Barrett et al., 2004; de Ridder et al., 2004; Lee et al., 2006; West, 2010; Kijima et al., 2011), it is important to understand the underlying factors governing the household labor allocation decisions to better promote agricultural productivity. This constitutes an important path for achieving agricultural intensification and, therefore, food security, as most households in this region mainly rely on agriculture for their livelihood.

However, the primary factors leading to differences in labor allocation are not only multifaceted, ranging from gender differential impact to social norms, but can also be location specific. Such a complexity of the household labor allocation decision-making highlights the challenges faced by development practitioners in this region to improve aggregate measures of household welfare in contexts where intra-household dynamics can be location-specific. This emphasizes the need for continuous research efforts in understanding household production decision making in these regions for successful development policy implementation.[2]

The current study aims to contribute to this small but growing literature using plot-level data to

[2] Using household plot level data from Burkina Faso, Kazianga and Wahhaj (2013) show that plots controlled by the head of household benefit from higher levels of labor input provision and achieve higher crop yields relative to plots controlled by other household members. In a similar study carried out by Guirkinger and Platteau (2014) in Mali, the authors find the opposite to be the case, with farmers devoting greater energy to their own individually managed plots compared to the collective plots

provide an alternative explanation of plausible sources of differences in labor allocation among extended family households in the Segou region in Mali. Households in this region jointly farm collective plots, which are controlled by household heads, with output and labor shared by all family members, while managing their own individual plots, with output and labor shared by immediate family members only.

The theory on collective farming predicts that this type of production organization is likely to lead to moral hazard on the collective plots (Israelsen, 1980; Carter, 1984; Meyer, 1989). Common recounted issues are coordination and supervision problems which lead to low input provision and, consequently, to low levels of output in the production of collective goods (Lin, 1987; Mcmillan, 1987). Indeed, this theory is supported by existing empirical evidence among rural households in another region in Mali (Guikinger and Platteau, 2014).

Preliminary empirical results in the current paper, however, provide evidence that depart from this theory. Specifically, using a two-wave household panel data collected in 2009 and 2012 with a unique feature that clearly distinguishes collective plots from individual, the study shows with compelling evidence that collective plots receive significantly much more labor per unit of land and present higher crop yield performance relative to individual plots.[3]

The paper makes the claim that the higher labor allocation on the collective plots can be attributed to motives for ex-ante risk mitigation for these households, to insure themselves against production risk. Following the same strategy as in Dillon et al. (2011), rainfall variability is used as a proxy for production risk. Specifically, rainfall variability is computed as the coefficient of variation of rainfall over a period of twenty-seven years (1981-2007) for each village in the sample.

The view of collective farming among extended family members as risk mitigation strategy has been explored theoretically but with sparse empirical application. One of the very few studies is by

[3] The results remain robust through alternative econometric specifications and sample restrictions, even after limiting the sample to the same individuals simultaneously managing collective plots and their own individual plots.

Rosenzweig and Wolpin (1985) with a focus on variation in farm profits by family structure.[4] The current work focuses on the importance of the role of labor, as a productive factor, by taking a more microeconomic analysis approach –that is, plot-level labor allocation –when production uncertainty due to weather variability exists. To my knowledge, no existing empirical work has looked at the links between ex ante exposure to production risk and intra-household plot-level labor allocation.[5] Collective farming among extended households is also prevalent in other West African countries, such as Burkina Faso (Kazianga and Wahhaj, 2016). Many of these households share similar production characteristics and face the same insurance markets failure for consumption smoothing (Townsend, 1994; Dercon, 2002; Kazianga and Udry, 2006). Consequently, results from the current work would provide insight, not only in the context of Mali, but also could be generalized beyond the case of Mali.

The argument that collective farming serves as insurance against production risk due to weather variability may seem at first glance counter-intuitive, since rainfall variability is perceived as a covariate shock and, consequently, assumed to affect all plots in a given region in a similar manner. Nevertheless, the setting of the study area makes this arrangement mechanism suitable for ex ante risk mitigation. Specifically, rainfall, which usually occurs from May to September, constitutes the main source of water for plots in the region, as households have very limited access to irrigation. Timing of agricultural activities during this period is critical for crop yield performance (Sultan et al., 2005; Mishra et al., 2008; Cooper et al., 2008; West, 2010) and, consequently, the household's ability to secure food availability.

For these households, labor remains an important production factor (de Ridder et al., 2004; Moser and Barrett, 2003; Barrett et al., 2004; Lee et al., 2006; Kijima et al., 2011), making its availability crucial to avoid production shortfall. Securing labor availability becomes more critical when weather instabilities

[4] Rosensweig and Wolpin (1985) investigate differences in farm profit variation across intergenerational family households relative to families without elderly members. Kazianga and Wahhaj (2017) tackle the question of risk sharing among extended family members in Burkina Faso using consumption data. Also, the authors focus on ex post shocks, while the current works looks at ex exposure to risk.

[5] A close existing work looking at plot-level labor allocation is by Akresh (2008) but with a fundamental difference with the current work. Akresh looks at labor allocation across male and female plots following weather shocks (i.e., ex post to weather shocks), while the current study looks at labor arrangement, ex ante to weather variability.

are such that households must accelerate the execution of some specific agricultural tasks. However, households in these regions, as in most Sub-Saharan Africa, face labor constraints (Moser and Barrett, 2003; Lee et al., 2006; Barrett et al., 2008; Smale et al., 2013) because they are not able to hire labor either due to liquidity constraints or missing labor markets and must rely on their own members to satisfy their labor requirement. Additionally, high risk of moral hazard in hired labor makes family labor more favorable (Foster and Rosenweig, 1994; Bharadwaj, 2015)

Given that households composed of extended family members are usually large and likely to be heterogeneous, by farming collectively, it is possible for them to overcome the adverse impacts of weather instabilities. Particularly, they are likely to have a larger pool of labor, enabling them to apply "brute strength" labor when weather fluctuations leave them with a constricted period to execute some major agricultural activities, (Putterman, 1983; West 2010). In addition, heterogeneity of the extended household members allows them to take advantage of "age-specific labor force". Specifically, they are able to mobilize workers with different endowments with younger members being more physically productive in the field while elder members have experience in responding to weather instabilities (Rosenzweig and Wolpin, 1985). These factors make the ground for the central claim advanced in the current paper –that is, collective farming being perceived as an ex-ante risk mitigation strategy.

The remainder of the study is organized as follows: Section 1.2 presents the background of the study zone with a description of the study site and household structure as well as their agricultural production arrangement. Section 1.3 provides the conceptual framework regarding collective farming as an ex ante risk mitigation strategy. Description of the data source and sample restrictions are given in section 1.4 while descriptive statistics are presented in section 1.5. Section 1.6 provides the empirical approach. Regression results of labor allocation and crop yield performance across collective and individual plots are presented in section 1.7. Section 1.8 provides empirical evidence of motives for insurance against risk while section 1.9 concludes the paper with some policy implications.

1.2 Background

Mali is one of the world's ten poorest countries with about 60 percent of its population living in rural areas (World Bank, 2016) where agriculture is the main source of livelihood. The country is divided in eight regions among which the Segou region, the study zone of the current work. The Segou region (see red colored in Figure 1.1) is the second largest region of Mali (in terms of population). The agro-ecological zone of the region is the Sudano-Sahelian zone. The study covers four cercles in the Segou region: Bla, San, Segou, and Tominian (see Figure 1.2). While the region is well known for its fishery and pottery industries, the main economic activity in the rural area remains small-scale farming, where the family constitutes the main sources for agricultural labor due to missing or incomplete labor markets in these zones.

Figure 1.1 Map of Mali with the Segou region

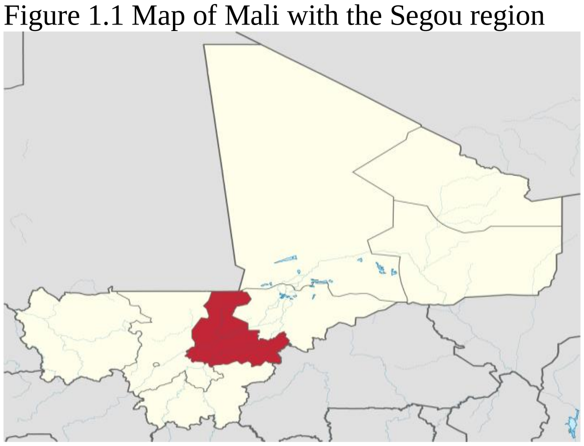

Figure 1.2 The "Cercles" included in the study zone

The ‘traditional’ farming household structure, as most rural households in Mali, is commonly composed of extended family members though there has been recently a rise in the formation of nuclear family households and, according to Guirkinger and Platteau (2014), a more individualization of farm management. The extended household is comprised of multiple nuclear households and is controlled by a senior male (the patriarch) who also has his own nuclear household. The production system within the extended household consists of collective plots controlled by the patriarch and individual plots controlled by adult males and married females. The patriarch allocates land to the latter.

Collective plots, named “foroba” (which means “big field” in Bambara), are generally larger than individual plots.[6] The decision maker on those plots is usually called the “chef des travaux” (work team leader). The work team leader tends to be the patriarch or one of the brothers or eldest sons of the patriarch (Becker, 1996). Individual plot managers are required to share their labor between the collective plots and their own plots. Part of the production from the collective plots may be sold for liquidity availability for agricultural input purchase for the next agricultural season and for other expenses within the extended household. The specific form of the distribution of the production to the nuclear households for their efforts provided on the collective plots depends on the extended household configuration.

The extended households may fall in two of the four household classifications by Beaman and Dillon (2012): (i) *common agriculture, dwelling and authority* or (ii) *common agriculture, food, dwelling, and authority*. In the first case, the production is distributed to the nuclear households in the form of grains. As for the second case, the production is kept in common granaries and extended household members share collective meals (Beaman and Dillon, 2012).[7] The sharing rule of the production in either case is based on need, rather than performance (Guirkinger and Platteau, 2014), which is very salient from the second case, where meals are taken collectively.

The existence of collective plots dates to the period prior to colonization, where members of the

[6] The “big fields” are formally referred to as *exploitation familiale* in Mali
[7] The other two classification by Beaman and Dillon (2012) are (i) common dwelling, authority, and common food and (ii) common dwelling, authority only.

same lineage collectively farmed the same land allocated by the “land chief”, who was a respected senior from the first family to settle in the area and had control over all the land in the village. The linear chief oversaw farming activities on the collective fields and was usually in charge of the redistribution of the production to individual households based on their needs (World Culture Encyclopedia, Mali). Men and women also had access to individual plots to maintain their financial autonomy. A land reform in 1986 allowed access to private land, which was largely adopted in the urban areas. However, land tenure in the rural area mostly remained collective (FAO, 2006). An important point to bear in mind is that formal land titles are almost inexistent in the rural areas of Mali. Land is the property of the State, and land users only have usufruct rights (USAID, 2010).

1.3 Conceptual framework

The study zone of the current work is characterized by drylands with limited access to irrigation, making rain-fed crop cultivation the main source of livelihood for households in this region. Yet, rain-fed crop production is highly sensitive to rainfall variability (Mishra et al., 2008; Cooper et al., 2008; and Sultan et al., 2005), making these households vulnerable to production uncertainty and risk. It may therefore be preferable for extended household members to secure the availability of sufficient labor on the collective plots to ensure higher levels of production to protect amongst themselves against food shortfalls.

Apparently, the argument that collective farming serves as insurance against production uncertainty due to weather variability by itself is uncertain. Given that variabilities in rainfall are perceived as covariate shocks and, consequently, assumed to affect all households in a given region in a same way, why would households dwelling in the same location use collective farming as ex ante risk mitigation? While this question cannot be answered definitively, there are nevertheless several factors that support the notion that collective farming can be viewed as an ex ante risk management strategy.

The risk of unpredictable labor bottlenecks during the agricultural season among nuclear households may be an important factor. Labor remains a major productive resource among households in sub-Saharan Africa as farmers tend to compensate for low (or even absent) non-labor input use by engaging in labor intensive practices such as land preparation, building yield enhancing or yield preserving technologies (manure, zai, stone-bunds etc.) and intensive weeding (de Ridder et al., 2004; West, 2010), *inter alia*. Because these practices are labor-intensive, their execution requires households to have access to a large pool of labor. Yet, it has been widely documented that labor availability remains a binding constraint among these households, due to their limited ability to hire labor either because of liquidity constraints or labor shortage at the pick of the agricultural season (Moser and Barrett, 2003; Barrett et al., 2008; Jack, 2013).

Labor constraints become exacerbated, with dire implications for the household's ability to secure food availability, when the environment is characterized by high weather uncertainty. Sultan et al. (2005) and Mishra et al. (2008) note that farmers in dryland areas tend to sow during early rains for richer soil nutrients and to reduce weeding labor requirements. However, early sowing may be risky because re-sowing may be required when it rains fewer than 10 out of 20 days following sowing (Sultan et al. (2005)). This weather fluctuation induces a large uncertainty in labor requirement of the nuclear household over the course of the growing season (Adams et al., 1997). Conversely, its impact on labor availability and the ability to mitigate its adverse impact among nuclear households may be heterogeneous, given that these households are likely to differ within the same extended household in terms of their demographic characteristics and farming experience.

To illustrate, consider an extended household where a father and his son are the heads of two nuclear households.[8] Obviously, the father is older and relatively less physically strong compared to the son.[9] Conversely, he (i.e., the father) due to his long-standing farming experience, is more likely to be well versed in strategic planning in the wake of weather instabilities (Rosenzweig and Wolpin, 1985). As a result, due to their heterogeneity in terms of their endowments, these two nuclear households present different levels of exposure even though they share the same weather attributes and may complement one

[8] Extended family households may also be formed by married brothers and their respective nuclear families
[9] This difference in age is supported in the current sample, as the average age of the heads of the nuclear households is about 42 while the corresponding figure for the heads of extended households is about 59 years

other to mitigate their vulnerability to risk .10 For example, Rosenzweig and Wolpin (1985) use district level historical rainfall data in India to show that districts with higher rainfall variability tend to have a higher concentration of intergenerational extended families.11 The authors find that in districts with higher rainfall variability, these intergenerational extended families achieve higher profitability and steadier gross returns compared to households with younger members because the former (i.e., intergenerational extended families) have elderly members who have specific knowledge allowing them to deal with adverse weather conditions.

Clearly, information in terms of agricultural practices can be shared across extended family members, which may undermine the claim that collective farming is favored for risk mitigation through gains from the experience of the elderly. One of the important aspects to consider here though, is the knowledge of farm-specificity, which is gradually instilled over the course of several years of farming the same farm plot (Rosenzweig and Wolpin, 1985).[12] For example, some specific areas on the same plot may need more yield enhancing or water management techniques relative to others, depending on weather conditions.[13] Also farmers are more likely to learn from those of similar age group (Conley and Udry, 2010). An implication for this is that agricultural knowledge transfer occurs mostly across rather than within households (Beaman and Dillon, 2014)[14]. This, combined with the farm-specificity knowledge

[10] Clearly, nuclear households may use other ways of ex ante risk mitigation such as seasonal migration, participation in non-agricultural income generating activities or off-farm labor supply. However, these strategies are unlikely to override the practice of collective farming as ex ante risk mitigation because they are not mutually exclusive with the later. Indeed, anecdotal evidence shows that many migrant household members in West Africa, especially in Mali and Burkina Faso, are required to return in their villages at the start of the agricultural campaign to supply labor on the family farm.

[11] The authors find that in districts with higher rainfall variability, these intergenerational extended families achieve higher profitability and steadier gross returns relative to households with younger members because the former (i.e., intergenerational extended families) have elderly members who have specific knowledge allowing them to deal with adverse weather conditions.

[12] Unfortunately, this claim of increasing farm-specificity knowledge due to several years of consecutive years of farming cannot be directly tested here because of non-availability of data on how long the plot has been exploited. However, I indirectly test this argument by looking at yield dispersions, over time, across collective plots –which are likely to have been farmed over several years –and individual plots

[13] For example, some area may be more prone to flooding in the wake of too much rain while other areas may be more severely affected following insufficient rainfall.

[14] The authors find that composting knowledge spillovers to women were more likely to occur across women from different households than within households with opposite gender.

assumption provide grant for my claim that the benefit from the elderly's experience for effectively responding to weather variability is more likely to occur through collective farming.

Another advantage of collective farming is that, owing to the larger size of the extended family households, they can access a large pool of labor (Putterman, 1983; West, 2010), allowing them to apply 'brute force' labor when weather fluctuations leave them with only a small window of time to carry out some specific activities. Agricultural activities must be carried out within a specific timeframe depending on rainfall conditions, and failing do so can have significant negative consequence for crop yield performance (Sultan et al., 2005; Mishra et al., 2008; Cooper et al., 2008; West, 2010) and, consequently, threaten food security. As a result, this guaranteed access to a large pool of labor that facilitates timely execution of the series of agricultural activities is an important feature that favors collective farming, especially when labor bottleneck is likely to occur at the peak of the agricultural season when no external labor is available for hire.

Also, collective farming allows extended family members to mobilize heterogeneous labor (male, female, and child labor), which increases the effectiveness of the timely execution of farm activities. To be more precise, access to heterogeneous labor permits delegation of different groups of laborers to specific agricultural activities, where they are the most efficient, further allowing them to accelerate the executions of agricultural tasks when needed. For example, while men are more efficient in activities that require physical strength such as plowing, women and children tend to be more specialized in transplanting and weeding (Boserup, 1970; Burton and White, 1984; Stone et al., 1995). As a result, such a specialization facilitated by collective farming increases the ability of extended households living in high rainfall variability areas to reduce exposure to potential crop failure.

These beneficial features of collective farming serve the basis for the central hypothesis in the current essay: households who are subject to weather variability will favor collective farming as an ex ante risk mitigation strategy. The ex-ante risk mitigation argument reflects the precaution of the nuclear households against production uncertainty by being engaged in collective farming, prior to the realization of the adverse event. This is different from the household's responses to weather shocks, which would be classified as ex poste risk copping strategies. For this reason, weather risk in the current dissertation is defined following the same approach in Dillon et al. (2011) as the variability of rainfall (rather than rainfall shocks), which captures the historical exposure of the household to production uncertainty.

For the first part of the empirical work, labor demand (expressed in person-days per hectare) on a given plot in the household will be derived from the following reduced form:

$$L = f(X, H, Z, Collective, \mu), \quad (1)$$

where X, H, Z, are vectors of plot, household, and village characteristics, and μ is a stochastic error term. Collective indexes whether the plot is collectively farmed. Differences in labor allocation across collective and individual plot will be captured by $\frac{\partial L}{\partial (Collective)}$. If labor is allocated equally across collective and individual plots after controlling for all relevant plot characteristics, then this term should be zero (Udry, 1996; Kazianga and Wahhaj, 2013). Labor allocation (in person-days per hectare) will be disaggregated by male, female, and child labor, as labor productivity is likely to differ by type of labor. For instance, with the same number of workers, amount of time, and land size, the productivity obtained from children is likely to be lower relative to the productivity obtained from men. The same reduced form will be used to investigate labor heterogeneity, in which case, L is a binary outcome taking 1 if mixed labor is applied on the plot labor (i.e., if men, women, and children work on the plot) and 0 otherwise.

To test the main research contribution of this paper–that is, the claim that collective farming constitutes an ex-ante risk mitigation mechanism, an interaction term between rainfall variability and the binary variable Collective is introduced in equation (1), leading to the following reduced form:

$$L = f(X, H, Z, Collective, [CV\_rain] * [Collective], \mu), \quad (2)$$

where CV rain, measures rainfall variability. Rainfall variability is captured by the coefficient of variation of rainfall, measured as the historical standard deviation divided by the historical rainfall mean for each village over a period of twenty-seven year (1981 to 2007). Rainfall variability in village v is defined as $CV_{rain_v} = \frac{SD_v}{\bar{x}_v}$, where $SD_v = \sqrt{\left(\frac{1}{T}\sum_{t=1}^{T}(x_{tv} - \bar{x}_v)^2\right)}$ is the historical standard deviation and

$\bar{x}_v = (\frac{1}{T}\sum_{t=1}^{T} x_{tv})$ is the historical rainfall mean, both computed over the period of 1981 to 2007 in village v. For each of these years, rainfall variability is computed for crop cultivation season (May through September).

The main proposition tested is that labor allocation (number of person-days per unit of land) is higher on collective plots among households in sites with greater rainfall variability. Formally, $\frac{\partial L}{\partial([CV\_rain]*[Collective])} > 0$. This would be consistent with the assumption that collective farming constitutes an ex ante risk mitigation strategy, which makes households allocate more labor on these plots. It is important to reiterate that the purpose of this paper is not to show that extended households devote more labor on the collective plots following weather shocks. What this paper does is to show that households living in places where weather fluctuations prevail, which constitute a major risk for production shortfall, will favor this type of production organization. As a result, ex-ante, they put in place a labor organization system that will systematically lead to higher labor allocation on the collective plots.

1.4 Data source and sample restrictions

1.4.1 Data source

The study uses the Saving for Change (SfC) project data15. The sampling was carried out in four "cercles" (Bla, San, Segou, and Tominian) in the Segou region. While parts of the region benefit from high access to irrigation –especially villages in the office du Niger and the cercle of Macina –the agricultural production in the study zone is dominated by the cultivation of rainfed subsistence crops. The main staple crops are millet and sorghum.

The data collection consisted of a first and second round surveys implemented in 2009 and 2012, respectively. Each round covered about 6,000 households in 500 villages. The survey used two household

[15] The primary objective of the SfC project was to evaluate a microfinance credit among rural women in the Segou region. The sampling consisted of randomly selecting a female adult in the age range 18-60. A question was asked whether the nuclear household of the selected woman shares agricultural production activities or consumption with another household. If the answer was yes, the nuclear household of the selected woman was identified as being part of a large household. Otherwise, the household was considered as a nuclear household.

classifications. The first is a nuclear household, defined as a person with his direct dependents. The second classification is an extended household formed by extended family members where multiple nuclear households live and carry out economic activities and food consumption together.

The survey used two questionnaires: one questionnaire for the nuclear household and another for the extended household. Only the questionnaire for the nuclear household was administered to households that are exclusively nuclear while both questionnaires were administered to those who cohabitate and carry out economic activities with extended family members. In the current work, plots belonging to the nuclear households are referred to as individual plots while those belonging to the extended household are classified as collective plots.

1.4.2 Sample restrictions

The SfC project data cover three types of nuclear households. The first category is the group of nuclear households who do not participate in any collective farming. These households constitute about 25 percent of the sample. The second type, which constitutes most the sample (about 60 percent), is formed by nuclear households exclusively engaged in collective farming with extended family members. By default, this group of households provides labor to the collective plots, as the region is characterized by missing agricultural labor markets. The third group, making 15 percent of the sample consists of households who participate in collective farming in addition to managing their individual plots.[16]

As the interest is to investigate differences in labor allocation and crop yields across collective and individual plots for plots planted to the same crop and in the same year within the same household, I restrict the sample to the third group of households –that is, those within which collective and individual plots coexist. Moreover, to eliminate any potential gender specific differential effects, I also exclude all female individual plots from the sample. Preliminary analysis of the full sample (Table

[16] The corresponding figure in Guirkinger and Platteau (2014) is about 26 percent. This is certainly because their study region (mainly, the Sikasso region) offers more irrigated agriculture such as the production of vegetable crops, which are more predominant on individual plots.

1A.1 in APPENDIX A) indicates that up to 71 percent of individual plots are controlled by female plot managers.[17] However, collective plots tend to be controlled by the head of household (who is mostly a male household member). Consequently, comparing labor allocation and crop yield across the two types of plot management structure without eliminating female individual plots will likely lead to outcomes being driven by gender-specific effects rather than by differences in plot management structure. Finally, the sample was also restricted to keep crops that are planted across collective and individual plots.

After these sample restrictions, which have the advantage to increase the internal validity of the study, the final sample retained for the study is about 15 percent of the full sample both at the plot and household level.[18] While this represents a small portion of the full sample, the comparison of the descriptive statistics with this restricted sample (see section 1.5) to the ones in Table 1A.2 (APPENDIX A) with the full sample of male plots reveals that the patterns of plot characteristics, crop choice, as well as labor allocation across collective and individual plots are preserved in the final restricted sample. Table 1.1 summarizes which subsample is used in each of the empirical specifications developed in section 1.6.

Table 1.1 Empirical specifications and their sub-sample

Subsample	Empirical specification
Households within which collective and individual plots coexist	Labor allocation across collective and individual plots using household-crop-year fixed effect
Household heads who simultaneously manage collective plots and their own individual plots	Labor allocation across collective and individual plots using plot-manager fixed effect
Households within which collective and individual plots coexist	Labor allocation across collective and individual plots using household-crop-year fixed effect controlling for rainfall variability
Household heads who simultaneously manage collective plots and their own individual plots	Labor allocation across collective and individual plots using plot-manager fixed effect controlling for rainfall variability
All categories of households	Likelihood of nuclear households' participation in collective farming
Households within which collective and individual plots coexist	Yield dispersion across collective and individual plots between the two survey rounds

[17] A robustness check of the main results with the full sample, with an indicator variable for plots controlled by women, provide consistent coefficient estimates of the key variables. Results are available upon request.
[18] Internal validity is increased by not only dropping female plots but also by dropping nuclear households without individual plots. By default, nuclear households without male individual plots are likely to allocate all their labor to the collective plots and failing to drop such households will overstate the labor gap across collective and individual plots.

1.5 Descriptive statistics

The descriptive statistics on plot characteristics and crop choice at the plot level across individual and collective plots are presented in Table 1.2. The results show that collective plots are significantly larger than individual plots. Also, land tenure and crop choice significantly vary across the two types of plot management structure. A higher proportion of collective plots tend to be grown to grain crops while the opposite is observed for vegetable crops. The most predominant grain crops are millet and sorghum and this is consistent with nationally representative data (USAID-Mali, 2008, World Bank, 2014). The proportion of plots grown to peanut is also high for both collective and individual plots.

The statistics show that the use rates of both organic and inorganic fertilizer as well as herbicide/pesticide are significantly high for collective plots relative to individual plots. Fertilizer (either organic or inorganic) application is labor-intensive in terms of the time needed for its application, increased weeding efforts, and more time needed for harvest (assuming fertilizer use increases yields). Conversely, herbicide use significantly reduces weeding efforts. These relationships between technologies and their differential labor requirements can have important implications for labor allocation across these plots, which is further discussed in section 1. Note that despite recent findings on a sharp increase in the use of herbicide in another region in Mali (Haggblade et al., 2017), only about 4 percent and 6 percent of individual and collective plots, respectively, receive herbicide application in the current sample.

There are also significant mean differences in soil types across collective and individual plots. However, as shown in Table 1A.3, these differences in soil types by plot management structure disappear once statistics are computed conditional on crop choice, especially for grain crops. This suggests that the observed differences in crop choice are driven by differences in soil quality. If soil characteristics are already embodied in crop choice, the concern of omitted variable bias due to unobserved differences in soil quality across collective and individual plots should be lessened once crop fixed effects are controlled for.[19] Furthermore, the proportion of plots with companion crops is significantly higher on the collective

[19] Plot-level regressions (results not presented here) of soil type on the indicator variable *collective* controlling for plot size and plot tenure show no impact of plot management structure on soil quality.

plots. Given that labor allocation is recorded at the plot-level for the main crop on the plot, this may inflate the amount of labor spent on the production of the main crop. To ensure that the main results are free from bias driven by this potential source of confounding factor, I check the robustness of the results after excluding these plots from the sample. The results remain consistent with the initial findings.

Table 1.2 Plot characteristics, crop choice, and inputs across collective and male individual plots

	Individual plots (N=1,703)		Collective plots (N=5,194)		
Variables	Mean	SD	Mean	SD	P-value of diff.
Plot size	0.89	0.94	2.26	2.68	0.00
Soil type					
Clay soil	0.31	0.46	0.35	0.48	0.03
Clay & sandy mix	0.38	0.49	0.34	0.47	0.01
Sandy soil	0.28	0.45	0.28	0.45	0.75
Gravel	0.03	0.18	0.03	0.18	0.83
Household owns plot	0.96	0.19	0.98	0.13	0.00
Main source of water is rain	0.98	0.12	0.98	0.15	0.11
Crop choice					
Millet	0.15	0.35	0.28	0.45	0.00
Sorghum	0.1	0.31	0.2	0.4	0.00
Maize	0.06	0.24	0.1	0.31	0.00
Rice	0.05	0.22	0.09	0.28	0.00
Peanut	0.47	0.5	0.11	0.32	0.00
Beans	0.03	0.17	0.03	0.16	0.73
Chickpeas	0.02	0.15	0.04	0.21	0.00
Fonio	0.04	0.19	0.09	0.29	0.00
Sesame	0.09	0.28	0.05	0.22	0.00
Plot has companion crop(s)	0.22	0.41	0.31	0.46	0.00
Inorganic fertilizer (1=yes)	0.11	0.32	0.29	0.45	0.00
Organic fertilizer (1=yes)	0.26	0.44	0.31	0.46	0.00
Herbicide/pesticide (1=yes)	0.04	0.189	0.06	0.23	0.00

Plot level observations. Sample restricted to households within which collective and male individual plots coexist. Top and bottom 1 percent of plot size and outcome variables dropped from sample

The significant differences in means in plot size across collective and individual plots raises the concern of whether there is any overlapping between the two types of plot management structure. Having an overlapping is important for linear controls to appropriately account for differences in plot size across collective and individual plots.

Figure 1.3 presents plot size distribution by plot management structure. As expected, there is high density of individual plots with small plot area, while the opposite is observed for collective plots. The distributions presented in Figure 1.4 reveal that collective and individual plots tend to overlap mostly for plot size smaller than 9 and 4 hectares, respectively for grain and non-grain crops. The figure also reveals that only a very few number of observations do not overlap across collective and individual. Yet, there is still a concern that differences in yield and labor allocation by plot management structure could be driven by the larger plot size of collective plots that do not overlap with individual plots. To ease this concern, I ran additional regressions by restricting the sample to plot size not greater than 9 and 4 for grain and non-grain crop plots, respectively.

Figure 1.3 Plot size (ha) distribution across collective and individual plots (all crops)

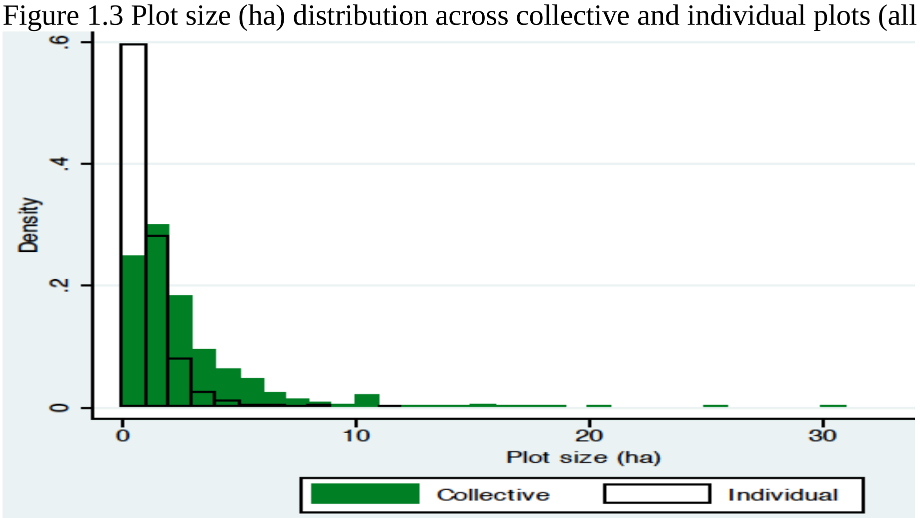

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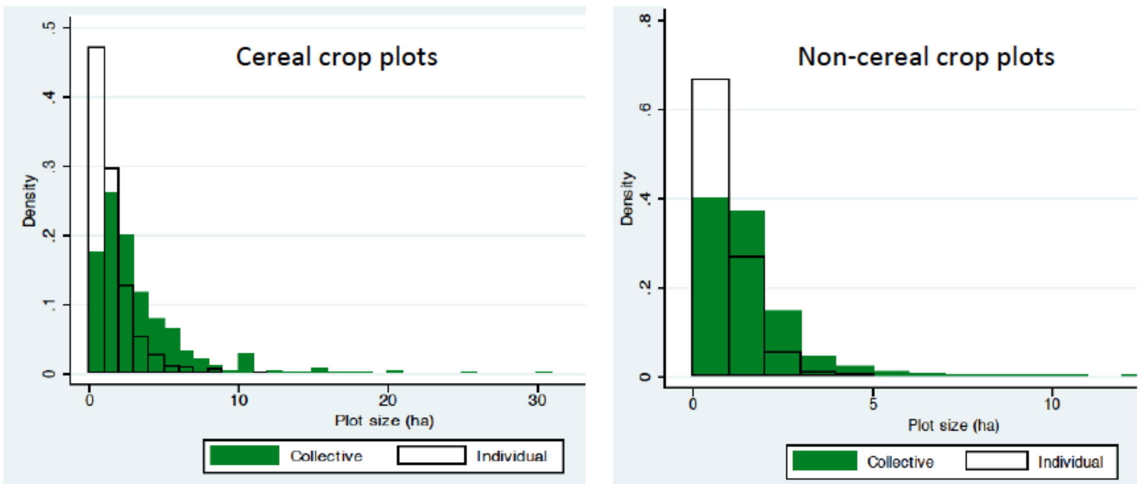
Figure 1.4 Plot size (ha) distribution across collective and individual plots by grain and non-grain crops



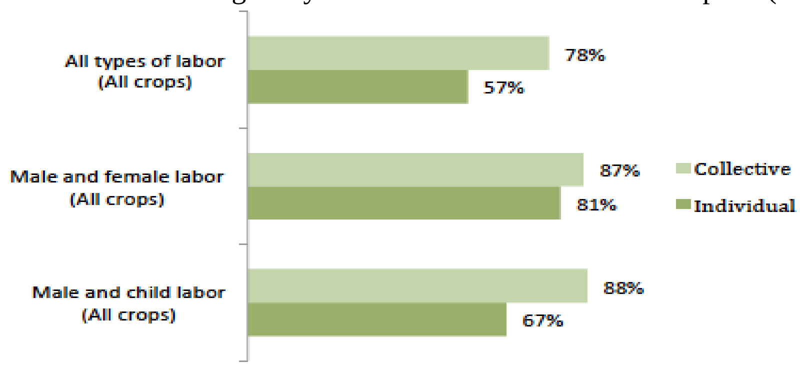
The dependent variables are presented in Table 1.3. Labor variables in terms of heterogeneity of laborers (male, female, and child) are binary outcomes. Labor intensity (total labor, male, female, and child labor) are all expressed in number of person-days per hectare while yield is expressed in monetary value (in 1,000 CFA per hectare).[20]

Table 1.3 Labor allocation across collective and male individual plots

	Individual plots (N=1,703)		Collective plots (N=5,194)		
Variables	Mean	SD	Mean	SD	P-value of diff.
Labor heterogeneity					
Plot receive male and female labor=1	0.81	0.39	0.87	0.33	0.00
Plot receive male and child labor=1	0.67	0.47	0.88	0.33	0.00
Plot receive all 3 sources of labor=1	0.57	0.50	0.78	0.41	0.00
Labor intensity					
Total labor (person-days/ha)	107.62	97.77	105.79	84.49	0.59
Male labor (person-days/ha)	55.65	54.91	51.74	42.69	0.03
Female labor (person-days/ha)	27.25	35.38	25.53	28.43	0.13
Child labor (person-days/ha)	24.87	36.15	28.55	32.22	0.01
Yield (1,000 FCFA per ha)	265.90	246.57	189.90	182.50	0.00

Plot level observations. Sample restricted to households within which collective and male individual plots coexist. Top and bottom 1 percent of continuous variables dropped from sample.

Figure 1.5 Labor heterogeneity across collective and individual plots (All crops)

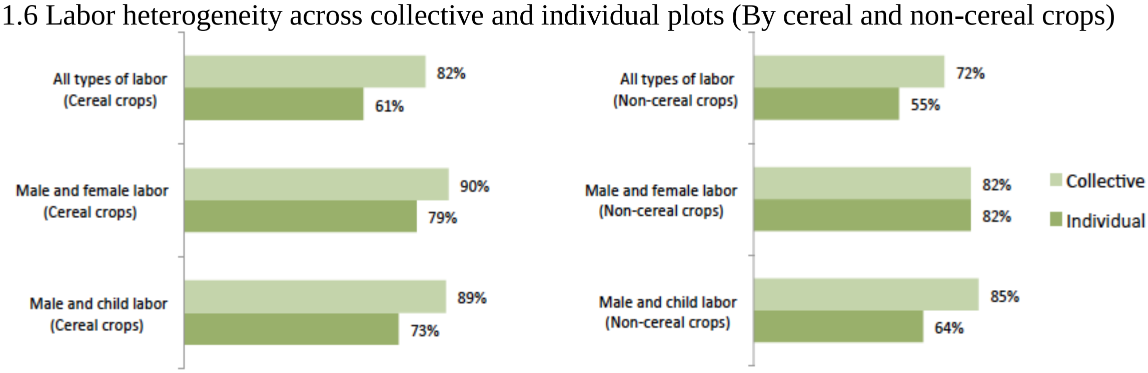


[20] CFA: Communauté Financière Africaine. The exchange rate at the time of the surveys was approximately $1US=500 CFA francs. Child labor is labor allocation by members who are between 5 and 17-year-old.

The statistics on labor heterogeneity, which are graphically illustrated in Figure 1.5, show that collective plots tend to receive more heterogeneous labor (i.e., receive more labor from men, women, and children) compared to individual plots. Note that all plots receive male labor since the sample has been restricted to male controlled plots only (see sample restrictions in section 1.4). The illustrations by grain and non-grain crops in Figure 1.6 (statistics not included in Table 1.3) show that the differential heterogeneity of labor across collective and individual plots is much higher for grain crops, which constitute the main staple food for these households. This hints that collective farming primarily favors the production of these crops, which would be consistent with the claim that households engage in this practice to guarantee their food security.

Conversely, individual plots tend to be more intensively farmed with male and child labor relative to collective plots, though there is no statistical significant difference in total labor allocation. Also, individual plots achieve higher yields than collective plots. This indication of higher labor allocation and crop yields on the individual plots is certainly because these statistics are mean values and do not take important factors such as crop choice and plot characteristics into account.

Figure 1.6 Labor heterogeneity across collective and individual plots (By cereal and non-cereal crops)



1.6 Empirical model

In this section, I specify multiple econometric models to test the two main reduced forms developed in section 1.3. The first set of specifications, which corresponds to the reduced form in equation (1) is to investigate labor allocation across collective plots and individual plots. Crop yield performance is also estimated by plot management structure in this set of specifications. Second, to show that collective farming serves as an ex-ante risk mitigation strategy, I introduce historical rainfall variability in the specifications, which corresponds to the reduced form in equation (2) to investigate how the gap in both labor allocation and crop yield between collective and individual plots varies across sites with different levels of rainfall variability. Finally, a linear probability model is developed to test the likelihood of participation in collective farming by nuclear households depending on the historical rainfall variability.

The main identification strategy applied in the specifications for labor allocation and crop yield performance is the household-crop-year fixed effect approach (HHCYFE), which is constructed as a unique identifier for each household by combining the household identification number, crop code, and the year indicator. The motivation for the use of the HHCYFE is that several unobservable and unobserved factors other than weather variability may influence the household's labor allocation decision across these plots. The use of the Household-Year-Crop Fixed Effects (which keeps much of these factors constant within households) presents a great potential to free the estimates of the key variables from plausible omitted bias (Udry, 1996).

1.6.1 Specifications with household-year-crop fixed effect

The empirical specification for estimating labor allocation across collective and individual plots follows the same strategy originally applied by Udry (1996), which was motivated by the collective model of the household developed by Browning and Chiappori (1998). Udry (1996) argues that if the same production technology is used on plots within the same household, then conditional on plot characteristics and crop choice, the amount of labor allocated across these plots should not be different.[21]

Labor demand across collective and individual plots within the same household in the same year, and for the same crop is defined as:

$$D_{hkjt} = X_{hkjt}\beta + \gamma Collective_{hkj} + \delta_{hkt} + \epsilon_{hkjt} \quad (3)$$

where D_{hkjt} is specified as either a binary indicator for labor heterogeneity or a continuous variable for the intensity of labor expressed in person-days per hectare on plot j of household h planted to crop k in year t. There are three separate specifications when D_{hkjt} is a binary variable and are defined as follows:

D_{hkjt} =1 if plot receives a mix of male, female, and child labor and 0 otherwise

D_{hkjt} =1 if plot receives a mix of male and female labor and 0 otherwise

D_{hkjt} =1 if plot receives a mix of male, and child labor and 0 otherwise.[22]

Recall that all plots receive male labor because the sample has been restricted to male plots (see section 1.4 for sample restrictions).

Four estimations are carried out for labor intensity (total, male, female, and child labor) all expressed in logs of person-days per hectare.[23] The disaggregation of labor by labor source is important in the sense that labor quality differs between men, women, and children. For example, if there are several children working on a plot, the intensity of labor allocation for that plot would be high, though it may not be as productive as a corresponding smaller figure provided by men on another plot of similar characteristics.

X_{hkjt} is a set of the observable characteristics of plot j, δ_{hkt} is a household-crop-year fixed effect; and $Collective_{hkj}$ is an indicator variable for collective plots (1 if a collective plot and 0

[21] See Udry (1996) for a formal description of the theoretical model

[22] As described later in this section, the sample is restricted to male plots. Consequently, all plots receive male labor. So, the case where plots receives a mix of female and child labor only does not apply.

[23] An alternative specification to the logarithmic function is the Inverse Hyperbolic Sine transformation (ISH). The advantage of this functional form is that it does not involve arbitrarily attributing non-zero positive values to observations with missing values. Therefore, as a further robustness check of the main findings, I apply the IHS transformation to the outcome variables. The results, available upon request, are similar to the main findings.

otherwise). Plot characteristics include plot size to control for economies of scales. I also control for soil type, as labor productivity may be correlated with soil quality and, therefore, may affect the household labor allocation decision (Fafchamps, 1993; Lamb, 2003; Dillon and Barrett, 2017). Plot tenure (owned by household or rented) is also controlled for given the large literature on the correlation between plot tenure and input investment (Hayes, 1997; Gebremedhin and Swinton, 2003; Goldstein and Udry, 2008; Quisumbing, and Pandolfelli, 2010; Teklewold et al., 2013).[24] Input use (mainly organic and inorganic fertilizer and herbicides) are also included as controls.[25] A positive sign of $\hat{\gamma}$ would be evidence that collective plots receive intensively more labor (or are more likely to receive a mix of labor for the case when D_{hkjt} is a binary indicator) than individual plots.

In principle, labor demand would include household characteristics such as the manpower of the household proxied by the number of adults in the household (Reardon, 1997; Barrett et al., 2004, Masakure and Henson, 2005; Peterman et at., 2014), access to markets, land prices and wages (Benjamin, 1992, Key et al., 2000, Taylor and Adelman, 2003; Barrett, 2008, Dillon and Barrett, 2017) in order to account for differences in shadow prices of production factors across plots within the same household as well as across households. These factors are assumed constant within households for a given year and given that the empirical strategy considers plots within the same household and controls for household-crop-year fixed effects, such factors are indirectly accounted for (Udry, 1996).

Note that all plots controlled by female-plot managers are dropped from the sample to eliminate any gender-differential bias. Furthermore, since the empirical approach investigates labor use on crops simultaneously grown across collective and individual plots within the same household and in the same year, the sample is restricted to households that participate in collective farming in addition to managing

[24] Plots managed under sharecropping are dropped from the sample as they only represent about 0.3 percent of the sample.
[25] The inclusion of input use controls for differences in the use rates of these inputs across collective and individual plots. Yet, their inclusion also raises a concern of a reverse causality between the decision to apply these inputs and labor endowment. To alleviate this concern of potential endogeneity, I run the regressions after dropping the sample of plots where these inputs are applied. The results, presented in Table 1B.1 and Table 1B.2, remain consistent with the main findings, both for labor allocation and crop yield.

their own male individual plots (see section 1.3 for more details on the categories of households in the sample).

In addition to investigating labor allocation, I also estimate yield differences to examine whether gaps in labor allocation will be reflected on yields. Assuming the same production technology across collective and individual plots, the specification for crop yield is defined as

$$Q_{hkjt} = X_{hkjt}\beta + I_{hkjt}\varphi + \gamma Collective_{hkj} + \delta_{hkt} + \epsilon_{hkjt} \tag{4}$$

Q_{hkjt} is the log of yield on plot j planted to crop k in year t by household h.

$I_{hkjt}\varphi$ is a vector of inputs, mainly organic and inorganic fertilizer and herbicide.[26]

If crop yield does not vary across collective and individual plots within the household, then γ = 0; that is, yield on a plot should not depend on plot management structure (i.e., whether collectively or individually managed) after controlling for relevant factors that may influence yield.

A shortcoming in the current empirical specification is potential selection bias in plot management structure that may influence the household's decision in its productive resource allocation and crop yield performance across collective and individual plots.[27] The same issue of omitted variable bias is also present in previous work striving to investigate intrahousehold resource allocation across different plots within the same household (Kazianga and Wahhaj, 2013; Udry, 1996; Goldstein and Udry, 2008 among others).

This concern of potential selection bias of plot management structure is intensified in the current study because of lack of information on distance to plot location and plot topography. Plots located closer to the dwelling of the household may receive more care due to easy access. Conversely, households may work more diligently on plots located at a greater distance to compensate for travel time (Kazianga and Wahhaj, 2013). With respect to plot topography, it has been shown that plots with uppermost

[26] The common technology assumption is motivated by the fact that production technology may vary across crops, but not across individual and collective plots as long as the same crop is planted across these plots within the same household and in the same agricultural season (Udry, 1996).
[27] Ideally, one would control for plot fixed effects. Unfortunately, such approach is not feasible because plots are not tracked over time.

toposequence are likely to be less productive relative to plots with nearest bottom toposequence (Steiner, 1998; Shorr, 2000; Guirkinger et al., 2015). If both plot location and plot topography are systematically correlated with plot management structure, failing to include them in the regressions will lead to biased estimates of γ.

However, existing empirical evidence suggests that farmers tend to make their crop choice contingent on plot characteristics such as soil type, plot location, and plot topography (Udry, 1996; Steiner, 1998; Shorr, 2000; Guirkinger et al., 2015). Though I lack data on plot location and plot topography, I show in Table 1A.3 (APPENDIX A) that conditional on crop choice, all available soil characteristics are fairly balanced across collective and individual plots, especially for grain crops. And, since I control for household-crop-year fixed effect in my regressions, the estimates of γ will condition on the main factors that are highly related to unobserved plot characteristics and therefore I see the estimates of γ as being largely free of these omitted variables bias.

There is still a concern of systematic differences in plot characteristics across collective and individual plots, especially for non-grain crops, based on the statistics in Table 1A.3 (in APPENDIX A). To account for these significant differences, separate regressions are run for all crops, grain crops, and non-grain crops. More importantly, three alternative econometric models (Models 1, 2, and 3) are specified by gradually adding plot characteristics for some sensitivity analysis. Specifically, Model 1 includes the indicator Collective and plot size only (in addition to controlling for household-year-crop fixed effects), Model 2 adds input use and plot ownership, while Model 3 adds soil type. The motivation behind these different specifications is to observe how sensitive yield differences across collective and individual plots are to the inclusion and omission of available plot characteristics. This allows to indirectly assess how serious the issue of the omitted unobservable plot characteristics is likely to be.[28] Fortunately, the results of the sensitivity analysis do not suggest any correlation between unobservable plot characteristics and crop yield. Nevertheless, this concern of lacking comprehensive plot physical

[28] The same strategy is used by Udry (1996) and Kazianga and Wahhaj (2013).

characteristics must remain a caveat in the current study.

1.6.2 Specifications with plot-manager-year fixed effect

The empirical specifications presented so far do not account for plot manager fixed effects because not all individuals concurrently manage individual and collective plots. Yet, plot manager characteristics may influence access to inputs and, consequently, crop yield performance (Ondersteijn et al., 2003; Foltz, 2004; Qaim et al., 2006; Barrett et al., 2008), as well as plot management structure (collective versus individual) such that the coefficient estimates on Collective may suffer from bias due to omitted plot manager effects. To address this issue, I impose another sample restriction and run additional econometric specifications.

Specifically, I restrict the sample to individuals (namely the heads of extended households) who control their own individual plots and collective plots at the same time. Using this restricted sample, I develop another specification where the household-year-crop fixed effect is replaced with an individual-year fixed effect. Such a specification with a sample restricted to individuals simultaneously controlling their own individual plots and collective plots constitutes a powerful way to demonstrate the robustness of the main findings. Given that collective plots tend to be exclusively managed by the head of household, who is inherently different from the other household members, being able to control for the plot manager's unobserved characteristics removes concerns related to possible correlation between plot manager characteristics and access to labor as well as crop yield performance.

Note that, including individual-year fixed effects means that I also control for individual characteristics that vary year to year (i.e. are time variant in addition to time invariant). This controls for anything that is unobserved and specific to an individual in a given year (e.g. changes in access to credit and input markets or productivity that might change from year to year within an individual). As a result, the specifications using individual-year fixed effects identifies the gap between collective and individual plots of off comparisons across these types of plots within an individual in each year.

Limiting the sample to the heads that simultaneously control their own individual plots and collective plots has another advantage beyond relieving the concern of omitted variable bias due to differences in the identity of the plot manager. As I highlight above, one of the concerns about potential selection bias of plot assignment as individual versus collective plots is that the head of household may systematically allocate less productive plots to junior members for individual farming. This is especially of a concern in the current work as plot characteristics display significant differences for non-grain crops across collective and individual plots. However, given that the head controls land allocation, it is unlikely that the later will allocate land of poor quality to himself for his own individual farming and, therefore, it is reasonable to expect that the head will choose a portion of land that is at least as productive as the portion of land used for collective farming. As a result, estimates of the coefficients on collective indicator are less likely to suffer from upward omitted variable bias in the restricted sample.

Lastly, investigating labor allocation and crop yield performance across collective and individual plots controlled by the same person provides a powerful way to explore whether it is plot management structure (i.e., collective versus individual) or plot manager identity that matters the most. To be more precise, if the identity of the plot managers across collective and individual plots matters, then there should be no differences in labor allocation and crop yields after restricting the sample to individual simultaneously controlling the two types of plots.

The empirical strategy using the sample of heads is specified in equations (5) and (6) for input allocation and crop yield, respectively.

$$D_{hjt} = X_{hjt}\beta + K_j\omega + \gamma Collective_{hj} + \delta_{iht} + \epsilon_{ihjt} \tag{5}$$

$$Q_{hjt} = X_{hjt}\beta + K_j\omega + I_{hkjt}\varphi + \gamma Collective_{hj} + \delta_{iht} + \epsilon_{ihjt} \tag{6}$$

Precisely, D_{hjt} is the intensity of labor (total, male, female, and child labor) expressed in log person-days per hectare on plot j managed by the head of household h in year t. Q_{hjt} is crop yield performance expressed in log of production in kilogram per hectare. δ_{iht} is the plot manager year-fixed effect. Because the specifications in equations (5) and (6) include plot manager-year fixed effects rather than household-year-crop fixed effect, the additional term K_j, which the crop fixed effect, is included to control for the household crop choice portfolio.[29]

In this subsection, I used sample restrictions and alternative econometric specifications to check the robustness of the estimated differences in labor allocation and crop yield performance across collective and individual plots. As a result, even though there may be a selection bias on plot unobservable characteristics across these two types of plot management structure, it is unlikely that taking such factors into account would substantially alter the main results presented in this paper.

1.6.3 Adding weather variability to the household-crop-year fixed effect

In section 1.3, I claim that collective farming may constitute an ex ante risk insurance mechanism among extended family households. To empirically investigate this claim, I introduce rainfall variability represented by CV_rain_v in equations 7 and 8. Rainfall variability is captured by the coefficient of variation (CV) of rainfall, measured following Dillon et al., (2011) by taking the historical standard deviation divided by the historical rainfall mean for each village over a period of twenty-seven years.[30]

Formally, I estimate the following equations

$$D_{hkjt} = X_{hkjt}\beta + \gamma Collective_{hkj} + \kappa(CV\_rain_v \ * Collective_{hkj})$$

$$+\delta_{hkt} + \epsilon_{hkjt} \qquad (7)$$

and

$$Q_{hkjt} = X_{hkjt}\beta + I_{hkjt}\varphi + \gamma Collective_{hkj} + \kappa(CV\_rain_v \ * Collective_{hkj}) + \delta_{hkt} + \epsilon_{hkjt} \quad (8)$$

for labor demand and crop yield, respectively, where standard errors are clustered at the village level.

If collective farming is driven by motives for insurance against production risk, then households

[29] Ideally, equations (5) and (6) would control plot-manager-year-crop fixed effects rather than plot-manager-year fixed effects, which would provide a stronger identification, as they would allow estimate the gap between collective and individual plots for crops grown simultaneously across these plots by the same individual in the same year. However, such identification strategy would impose a strong restriction on the data, leading to very low variation across households.

[30] $CV\_rain_v = \frac{SD_v}{\bar{x}_v}, where \ SD_v = \sqrt{\left(\frac{1}{T}\sum_{t=1}^{T}(x_{tv} - \bar{x}_v)^2\right)}$ is the historical standard deviation and $\bar{x}_v = (\frac{1}{T}\sum_{t=1}^{T} x_{tv})$ is the historical rainfall mean, both computed over the period of 1981 to 2007 in village v.

living in sites with high weather variability will pool more labor on collective plots to secure food availability. As a result, the prediction is that $\kappa > 0$. Furthermore, if collective farming is used as an ex ante risk management strategy, households in sites with higher weather variability should be more likely to be engaged in collective farming. This assertion is tested through equation 9, defined as follows:

$$Collective\_farming_{hv} = \tau CV\_rain_v + G_v\xi + X_{hv}\omega + \epsilon_{hv} \qquad (9)$$

where $Collective\_farming_{hv}$ is a binary variable that takes 1 if household h is engaged in collective farming with extended household members in village v. The sample used here includes all the three types of households described in section 1.4. The full sample of household is used since the objective here is to estimate the probability of a household being engaged in collective farming. Because this estimation is carried out at the household level, the sample of plots is collapsed at the household level such that households where at least one collective plot exists will be considered as participating in collective farming.

Though the full sample is used, all female plots are dropped from the sample before putting the data at the household level. This is mainly due to two reasons. First, female plots are not included in any of the estimations in the previous sections due to concerns related to gender differential bias. Second and, most importantly, land distribution to female household members follows different norms than land allocation to male household members. Land is distributed to male through bloodline whereas women mostly obtain land through marriage. A nuclear household not participating in collective farming primarily obtains most its livelihood from the production from male plots, rather than female plots. Proceeds from women's plots are for their financial independence and for sometimes cooking small meals for their own children (Toulmin, 1986).

CV_rain_v in equation (9) is defined as above, X_{hv} and G_v are vectors of household and village characteristics likely to be correlated with the household decision to participate in collective farming, and ϵ_{hv} captures other exogenous shocks that affect the probability of household h being engaged in collective farming in village v. Household level characteristics are classified in terms of household demographics and asset holding. Demographics are represented by household size and the age of the head of the nuclear household. The underpinning reason for the inclusion of the head's age is to indirectly assess the assumption that participation in collective farming allows younger plot managers to benefit from the experience of the elderly members. As a result, since experience is likely to increase with age, the age of the nuclear household head is expected to be negatively correlated with the likelihood of participation in collective farming.

Constraints to land access partly due to missing land markets have been found to be positively correlated with collective farming among extended family members (Rosenzweig and Wolpin, 1985; Kazianga and Wahhaj, 2017). This is explored by including total land holding in equation 9. Furthermore, motives for economies of scale, especially for investment in indivisible agricultural equipment (Carter, 1987; Mathijs and Swinnen, 2001), may also favor collective farming. Consequently, draft animal ownership by the nuclear family household, which requires high financial capacity, is also included in equation (9) as asset holding to assess the robustness of the coefficient estimates of τ.

Village level covariates include the total number of households in the village, availability of formal credit in the village and whether the village experienced outmigration over the last ten years. Since these covariates are likely to be correlated with rainfall variability, estimations will be carried out with and without these variables to verify the consistency of the estimates of the key coefficient, which is τ. The prediction is that τ is expected to have a positive sign (i.e., $\tau > 0$). In other words, households in villages with high rainfall variability will be more likely to be engaged in collective farming.[31] Note that the full sample of household is used in this specification since the objective here is to estimate the probability of a household being engaged in collective farming.

Despite controlling for important village covariates that are likely to be both correlated with rainfall variability and the household decision to participate in collective farming, I must emphasize that this specification is only descriptive and thus does not establish a framework to determine a causal

[31] Recall that the type of risk referred to here is ex ante risk, rather than ex post risk. As a result, even though households in the same area share the same weather characteristics, collective farming may serve as an ex ante insurance mechanism among households who anticipate to face production risk due to weather uncertainty.

correlation between rainfall variability and the household decision to participate in collective farming. Nevertheless, the concern of endogeneity between the nuclear household's decision to engage in collective farming and village level characteristics is reduced by the inclusion of important village covariates in equation (9). Additionally, the statistics presented in Table 1A.4 in APPENDIX A show very little correlation between rainfall variability and the available village covariates. This hints that the results from the specification in equation (9) are unlikely to be strongly altered by other sources of village level confounding factors. Therefore, though only descriptive, findings from the current work would provide suggestive evidence that higher rainfall variability could lead households to engage more in collective farming as an insurance instrument.

1.7 Results: Labor allocation and crop yield

1.7.1 Results with household-crop-year fixed effects

The summary statistics in Table 1.2 show a large difference in plot size, crop choice, and plot tenure across collective and individual plots. In addition, the rates of organic and inorganic fertilizer as well as herbicide/insecticide, whose application has different implication for labor requirement, are significantly higher for collective plots. These significant differences in means may constitute possible sources of variation in labor allocation across the two types of plot management structure. Thus, these variables are included in the labor allocation estimation. While including these inputs controls for differences in their use rates across collective and individual plots, their inclusion also raises a concern of a reverse causality between labor endowment and the decision to use them. To check the robustness of the results to this potential endogeneity, I run the regressions after dropping the sample of plots on which these inputs are applied. The results, presented in Table 1B.1 and Table 1B.2 (see APPENDIX B) obtained with the corresponding sample remain consistent with the main findings, both for labor allocation and crop yield.

Other significant sources of variations in the household's labor allocation decision are market conditions such as input prices, wages, and access to credit. While these factors are not explicitly included in the regressions, they are taken into account through the household-year-crop-fixed effects, the same approach applied in existing similar empirical work (e.g., Udry, 1996; Kazianga and Wahhaj, 2013). Given the identification strategy, the sample is restricted to nuclear households that manage their own male individual plots concurrently with participating in collective farming. Furthermore, due to the gender differential bias in both input access and crop yield performance (see review by Quisumbing, 1996), which is corroborated in this study (see Tables 1C.1 and 1C.2 in APPENDIX C), all female plots are excluded from the sample to eliminate any gender differential bias.[32]

The results with respect to labor heterogeneity, where the outcome variables are expressed in binary terms, are presented in Appendix D, Tables 1D.1 and 1D.2. The estimation results for the intensity of labor allocation, expressed in the log of the total labor on the plot, are presented in Table 1.4. Since labor quality differs across men, women, and children, the results are provided for total labor as well as for male, female and child labor. Also, results are presented with the key variable only –that is Collective –before including the other covariates.

[32] A robustness check of the findings with the full sample (i.e., including female plots) presented in APPENDIX C provides similar with stronger coefficient estimates of the key variable (i.e., the indicator variable *Collective*)

Table 1.4 Estimation of log of labor allocation (person-days/ha) across collective and male individual plots

	Model 1: Without plot covariates				Model 2: With plot covariates			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Log(Total Labor/ha)	Total(Male labor/ha)	Log(Female labor/ha)	Log(Child labor/ha)	Log(Total Labor/ha)	Total(Male labor/ha)	Log(Female labor/ha)	Log(Child labor/ha)
Collective=1	0.163***	0.384***	0.082**	0.303***	0.384***	0.303***	0.480***	0.688***
	(0.034)	(0.038)	(0.057)	(0.069)	(0.039)	(0.043)	(0.063)	(0.081)
Log of plot size					-0.248***	-0.246***	-0.171***	-0.127***
					(0.023)	(0.026)	(0.041)	(0.045)
Organic fertilizer=1					0.095**	0.117***	0.015	0.052
					(0.037)	(0.040)	(0.059)	(0.063)
Inorganic fertilizer=1					0.02	0.009	0.113	0.037
					(0.043)	(0.046)	(0.074)	(0.075)
Herbicide / insecticide=1					-0.183**	-0.169	-0.20	-0.358**
					(0.093)	(0.104)	(0.182)	(0.169)
Household owns plot=1					0.126	0.08	-0.148	0.489**
					(0.141)	(0.141)	(0.225)	(0.224)
Clay & sandy soil (clay is omitted)					0.08	0.052	-0.001	0.204**
					(0.053)	(0.053)	(0.098)	(0.104)
Sandy					-0.062	-0.021	-0.119	-0.04
					(0.050)	(0.054)	(0.082)	(0.088)
Gravel					0.034	-0.029	-0.062	0.298
					(0.116)	(0.109)	(0.178)	(0.187)
HHCYFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,897	6,897	6,897	6,897	6,897	6,897	6,897	6,897
R-squared	0.0189	0.0036	0.0301	0.0983	0.1046	0.0773	0.0459	0.1126

Plot level observations. Robust clustered standard error at the household level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to households within which collective and male individual plots coexist. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample

There is a strong indication that collective plots are more intensively farmed than individual plots. This is shown by the positive and significant coefficient estimate of γ for not only total labor but also for any type of labor. Specifically, $\hat{\gamma} = 0.38$ in column 8 indicates that total labor allocation per hectare on collective plots is about 47 percent higher than the corresponding amount allocated to individual plots. Disaggregating labor allocation by source reveals that labor gap is much higher for female and child labor.

Other noteworthy findings in Table 1.4 are the opposite signs of the coefficient estimates on fertilizer and herbicide use. Specifically, the results indicate that fertilizer use (mainly organic fertilizer) is associated with more labor requirement while herbicide use, which reduces weeding time, significantly lowers the amount of labor allocated to the plot. These findings are strongly supported by the literature on the adoption of these technologies (Gianessi and Williams, 2011; Gianess, 2013).

The analysis by labor source shows that the higher labor requirement associated with organic fertilizer is significant for male labor. This support the view that adoption of organic fertilizer requires physical strength (production and transportation), making men more suitable for the execution of these tasks (Feng et al., 2010). In contrast to organic fertilizer, the major source of labor affected by herbicide use is child labor. This finding corroborates the claim that weeding activities are mostly performed by children.[33]

The higher labor amount applied on collective plots does not necessarily indicate that more effort is being applied on these plots relative to individual plots. As reported in the work of Guirkinger and Platteau (2014), individuals may be spending more time on the collective plots for only token contributions in order to fulfill collective labor participation requirements, and save their energy to work later on their individual plots. If the observed higher labor applied on the collective plots is real effort provision, then collective plots should achieve higher yields relative to individual plots.

Table 1.5 presents the estimation results of the monetary value of yield (from equation 4)

[33] Children are household members who are 5 to 17-year-old.

expressed in log terms.[34] As in the labor allocation regressions, yield is estimated controlling for household-year-crop-fixed effects. Note that Table 1.5 contains fewer numbers of observations relative to Table 1.4 as observations for yield variables are at the crop-level. Two important points must be highlighted here. The first is the presentation of the results for different samples of crops (Panel A for all crops, Panel B for grain crops, and Panel C for non-grain crops). The second point to be noted is the use of three different econometric models (Models 1, 2, and 3) in each of the three panels. Model 1 presents the results where I only control for the indicator *Collective* and plot size expressed in log terms. Given that yield increases with the use of both organic and inorganic fertilizer as well as herbicide use, and because descriptive statistics show significant differences in the application rates of these inputs, I control for the use of such inputs in Model 2 besides controlling for plot tenure.[35] Model 3 includes soil type, mainly whether the soil type on the plot is sandy, clay, clay-sandy mixed, or gravel (the omitted soil type being sandy soil).

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[34] Village level prices, recorded through community questionnaires at the survey times, were used to convert production into monetary value

[35] As noted earlier, the inclusion of these inputs raises a concern of endogeneity. The robustness of the results to this potential reverse causality is checked by running the regressions after dropping the sample of plots on which these inputs are applied. The results are presented in Table 1B.1 and 1B.2 for labor allocation and crop yield (see APPENDIX B), respectively, are consistent with the main findings.

Table 1.5 Estimation of log of yield (FCFA/ha) across collective and male individual plots

	Panel A: all crops			Panel B: grain crops			Panel C: non-grain crops		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Collective=1	0.288***	0.294***	0.293***	0.371***	0.359***	0.377***	0.299***	0.309***	0.305***
	(0.06)	(0.05)	(0.05)	(0.10)	(0.10)	(0.10)	(0.07)	(0.07)	(0.07)
Log of plot size	-0.190***	-0.203***	-0.198***	-0.146**	-0.147**	-0.151**	-0.324***	-0.337***	-0.327***
	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
Organic fertilizer=1		0.231**	0.231**		0.264**	0.313**		0.192	0.157
		(0.11)	(0.11)		(0.13)	(0.13)		(0.18)	(0.18)
Inorganic fertilizer=1		0.083	0.049		0.012	-0.026		0.047	-0.011
		(0.11)	(0.11)		(0.13)	(0.12)		(0.20)	(0.20)
Herbicide/insecticide=1		-0.213	-0.188		-0.41	-0.313		0.011	0.045
		(0.355)	(0.347)		(0.626)	(0.565)		(0.282)	(0.259)
Household owns plot=1		0.141	0.134		0.113	0.059		0.183	0.21
		(0.19)	(0.19)		(0.16)	(0.19)		(0.26)	(0.25)
Clay and sandy soil (clay is omitted)			-0.091			0.258			-0.303***
			(0.09)			(0.17)			(0.11)
Sandy			-0.254***			-0.227			-0.329***
			(0.09)			(0.18)			(0.11)
Gravel			-0.038			-0.255			-0.024
			(0.17)			(0.31)			(0.25)
HHCYFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,062	5,062	5,062	2,824	2,824	2,824	2,238	2,238	2,238
R-squared	0.043	0.051	0.061	0.055	0.067	0.097	0.067	0.072	0.092
Sample Mean (SD)	(Mean=11.692; SD=1.091)			Mean=11.595; SD=.941)			(Mean=11.815; SD=1.245		

Crop level observations. Robust clustered standard error at the household level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to households within which collective and male individual plots coexist. All specifications include household-year-crop fixed effects.
Top and bottom 1 percent of plot size and outcome variables dropped from sample. Village level prices recorded through community questionnaires were used to convert production into monetary value. FCFA: Franc Communauté Financière Africaine. The exchange rate at the survey times was approximately $1US=500 FCFA. Fewer number of observations relative to Table 1.4 because yield variables are at the crop-level.

The estimates of γ in Table 1.5 are positive and statistically different from zero at the 1 percent significance level across all the three models. Both the sign and the significance level of the coefficient remain robust even when crops are split into grain and non-grain crops (Panels B and C). The estimates of γ in the most exhaustive specification (i.e., Model 3) in Panels B and C in Table 1.5 (0.377 and 0.305, respectively) imply that grain and non-grain crop yields are about 46 percent and 36 percent, respectively, higher on collective plots relative to individual plots. The results also show that crop yield is decreasing in plot size, suggesting diminishing returns to land.[36]

Recall that the difference between Models 2 and 3 is the inclusion of soil type in Model 3. The reason for doing so is to observe how crop yield performance changes across individual and collective plots when soil observable qualities are controlled for. If soil quality is higher on collective plots, then failing to control for them is likely to bias upward the coefficient estimates in Model 2. Consequently, the magnitude of $\hat{\gamma}$ in Model 3, where such factors are controlled for, should be smaller relative to the ones in Model 2. Yet, comparing $\hat{\gamma}$ across Models 2 and 3 reveals almost no difference (Panel A) and if any, it (i.e., $\hat{\gamma}$) is slightly higher in Model 3 for grain crops (Panels B), suggesting that individual plots are at least as productive as collective plots with respect to soil observable characteristics.

Though these findings do not offer a definite ground to infer that collective plots are not inherently of better quality than individual plots, it seems less probable that the higher crop yield performance on collective plots is driven by better unobservable or unobserved soil quality on these plots relative to individual plots. These same alternative econometric specifications have been applied in previous empirical work to establish that female (or individual) plots are at least as productive as male (or collective) plots (Udry, 1996; Kazianga and Wahhaj, 2013).

Plot size, in Tables 1.4 and 1.5, is expressed in logarithm terms. Following Udry (1996) and Kazianga and Wahhaj (2013), regressions are run with plot size expressed in deciles. The results, presented in Table 1E.1 in Appendix E (see APPENDIX E), are consistent with those presented in Tables

[36] Plot size is expressed in log. Similar results are obtained using plot deciles.

1.4 and 1.5. Applying the Inverse Hyperbolic Sine transformation (ISH) to the outcome variables and plot size also provides similar results to the main findings.[37]

Furthermore, there is a concern that differences in yield and labor allocation across collective and individual plots could be driven by no overlapping between some collective and individual plots due to differences in plot size (see figure 1.4). To ease this concern, additional regressions are run by restricting the sample to plot size where collective and individual plots overlap. The results, presented in Tables 1F.1 and 1F.2 (in APPENDIX F) for crop yield and labor allocation, respectively, remain consistent with the main results.

Moreover, to test the robustness of the main results to a possible reverse causality between inputs that are potentially complement (i.e., organic and inorganic fertilizers) or substitute (i.e., herbicide) to labor, additional regressions are run after excluding all plots receiving such inputs. The results, presented in Tables 1G.1 and 1G.2, respectively for labor allocation and crop yield performance, are consistent with the main findings.

Finally, as shown in the descriptive statistics, the proportion of plots with companion crops is significantly higher for collective plots (see Table 1.2). This combined with the fact that labor is recorded at the plot-level, for the main crop on the plot, may lead to an overestimation of the intensity of labor on the collective plots. However, the results presented in APPENDIX G for plots with no companion crops, remain as the main findings, suggesting no major concerns about this potential source of a confounding factor.

1.7.2 Labor intensity and crop yield with plot-manager-year fixed effects

A unique feature of the data used in the current work is that it allows to distinguish the head's own individual plots from plots that are purely collective. To my knowledge, such a distinction has not yet been made in the existing literature dealing with similar questions (Kazianga and Wahhaj, 2013); Guirkinger and Platteau, 2014); and Guirkinger et al., 2015). The advantage of being able to observe and

[37] The advantage of the Inverse Hyperbolic Sine transformation is that, contrary to the logarithmic transformation, it does not involve arbitrarily attributing non-zero positive values to observations with missing values.

distinguish between the head's own individual plots and the collective plots he manages is threefold. The first is the ability to control for plot-manager-fixed effects, which provides a unique way to address the concern of omitted variable bias (such as that due to educational level, farming experience, and access to extension services) as well as his access to productive resources.

The second advantage is that by focusing only on plots managed by the household head, I can reduce potential bias due to endogenous plot allocation since the head is usually responsible for allocating plots to household members. For example, among plots managed by the household head, soil quality is likely to be similar on collective plots relative to individual plots because it is unlikely that the head will choose a plot of poor soil quality for himself. Finally, this feature of the data provides a unique way to study whether differences in labor allocation and crop yield across collective and individual plots are solely because collective plots are almost always managed by the head of household, who is likely to have more control over productive resources relative to the other household members. If this is the case, then we should not observe any statistically significant differences in input allocation and in yield after restricting the sample to collective plots and individual plots of household heads.

The results related to labor allocation with the restricted sample with specification without and with plot covariates are presented in Table 1.6. Because crop effects are not incorporated in the construction of the plot-manager-year fixed effects (PMYFE), in addition to controlling for plot characteristics and organic and inorganic fertilizer use, I also control for crop fixed effects.

Table 1.6 Estimation of log of labor allocation (person-days/ha) across collective and heads' individual plots using PMYFE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Log(Total Labor/ha)	Total(Male labor/ha)	Log(Female labor/ha)	Log(Child labor/ha)	Log(Total Labor/ha)	Total(Male labor/ha)	Log(Female labor/ha)	Log(Child labor/ha)
Collective=1	0.148***	0.086	0.495***	0.455***	0.373***	0.315***	0.625***	0.610***
	(0.047)	(0.053)	(0.092)	(0.107)	(0.047)	(0.052)	(0.095)	(0.112)
Log of plot size					-0.329***	-0.334***	-0.207***	-0.221***
					(0.028)	(0.032)	(0.049)	(0.048)
Organic fertilizer=1					0.119***	0.163***	-0.003	0.095
					(0.043)	(0.046)	(0.082)	(0.079)
Inorganic fertilizer==1					0.078	0.076	0.117	0.078
					(0.054)	(0.056)	(0.098)	(0.098)
Herbicide / insecticide=1					-0.072	-0.057	-0.038	-0.094
					(0.118)	(0.129)	(0.192)	(0.232)
Household owns plot=1					0.135	0.15	0.081	-0.132
					(0.196)	(0.217)	(0.261)	(0.216)
Clay & sandy soil (clay is omitted)					-0.05	-0.104*	-0.117	0.254*
					(0.056)	(0.059)	(0.106)	(0.136)
Sandy					-0.109**	-0.08	-0.142	0.064
					(0.050)	(0.055)	(0.090)	(0.112)
Gravel					0.039	0.019	0.018	0.328**
					(0.107)	(0.114)	(0.165)	(0.158)
PMYFE								
Observations	1,743	1,743	1,743	1,743	1,743	1,743	1,743	1,743
R-squared	0.075	0.045	0.114	0.052	0.209	0.175	0.134	0.079

Plot level observations. Robust clustered standard error at the household level in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Sample restricted to heads that control simultaneously their own individual plots and collective plots. Top and bottom 1 percent of continuous variables dropped from sample

The results show that collective plots are significantly more intensively farmed than the head's own individual plots, regardless of labor type and the model specification, except for male labor in Table 1.6, column 2. To be more specific, even when collective plots and individual plots are controlled by the same person, they (i.e., the collective plots) still receive significantly more labor relative to individual plots. The estimate of γ for total labor when all plot covariates are included is about 0.37 (Table 1.6, column 5). Since the dependent variables are expressed in log, this indicates a differential impact for collective plots on total labor allocation of approximately 45 percent. Disaggregating labor allocation by labor type reveals that labor allocation gaps are higher for female and child labor, which is consistent with the results obtained with the household-crop-year fixed effects (Table 1.4).

Consistent with the labor allocation results, crop yields with the restricted sample reported in Appendix H (see Table 1H in the appendix) are higher for collective plots. Specifically, I find that crop yields are approximately 46 percent and 34 percent higher on collective plots relative to individual plots for grain (Model 3, Panel B, Table 1.9) and non-grain crops (Model 3, Panel C, Table 1.9), respectively. The order of the differences is similar to the finding with the results presented in Table 1.6. The comparison of $\hat{\gamma}$ between Models 2 and 3 shows that the magnitude of the coefficient estimate remains almost of the exact size regardless of whether the type of soil on the plot is included or not. These results further support the argument that the large observed differences in yield are unlikely to be driven by omitted variables bias in soil quality between collective and individual plots.

The consistently positive and significant coefficient estimates of the indicator variable *collective* across the alternative econometric specifications and sample restrictions provides strong evidence that collective plots receive more inputs and present higher yield than individual plots. These findings are not in line with what it is generally predicted by the economic theory on collective action, which is low efforts provision in the production of collective goods. Indeed, with one exception (Kazianga and Wahhaj, 2013), an overwhelming majority of the empirical literature finds evidence that collectively managed farms suffer from low effort provision leading to lower overall output level (Putterman and DiGiorgio, 1985; Lin, 1987; Carter, 1987; McMillan et al., 1987; Guirkinger and Platteau. 2014).

As a result, a natural question arises from the current paper: Why do we find that collective plots are more intensively farmed? Particularly, given that the proceeds from the collective plots are for shared consumption within the household, what deters individuals from shirking on the collective plots and devoting more effort to their individual plots where they alone claim the farm's production? While it is not possible to offer a definite answer to these questions, I posit that motives for insurance against production risk partly explain these observed labor and yield gaps across the two types of plots management. This idea of collective farming being favored when production risk prevails has indeed been theoretically explored, but its empirical application, especially in West Africa, remains very limited.[38]

The underpinning assumption for the risk insurance claim is that collective farming can enable nuclear households to reduce production variability across years. I provide suggestive evidence for this claim in APPENDIX I, where a Chow test across the two groups of plots, on the effect of the time indicator variable on yield residuals, shows that changes in yield dispersions across the two survey rounds are significantly lower for collective plots relative to individual plots. This lower variation on yield dispersion across years on the collective plots provides somehow an insured agricultural output for extended household members. Collective farming may therefore be favored by households living in places with high weather unpredictability, which is a major source for production uncertainty. As a result, these households are likely to be inclined to allocate more labor on the collective plots relative to their own plots, where production uncertainty is higher. This assertion is empirically explored in the following section.

Certainly, there are other potential explanations for why collective plots are more intensively farmed than individual plots. Such justifications may include more tenure security on collective plots, though this mechanism is less plausible in the current context, given that the type of crops included in this study are all short-term rather than perennial crops.[39] In addition, because collective plots are more likely

[38] One of the few existing studies is the work by Rosenzweig and Wolpin (1985) in India.
[39] Also note that there are no formal land titles in rural Mali. Households only have usufruct right to exploit the land.

to be farmed by a group of workers, one may argue that this would lead to peer effects, inducing longer hours of work on the collective plots and, therefore, higher yield. This is not likely to be an important factor because it is also possible to have more than one worker on the individual plots. As a result, peer effects may rise on these plots as well. Economies of scale in terms of land exploitation can also be ruled out as plot size is included as a control in all specifications. However, economies of scale in terms of indivisible assets such as draft animal may incite participation in collective farming. This is explored in section 1.8. Finally, another plausible mechanism is social norms that may compel members from the nuclear households to provide labor on collective plots. This latter mechanism is more plausible but unfortunately, it cannot be tested with the available data.

1.8 Evidence for motive of risk insurance

Recall that the central assumption in this study is that the higher labor allocation on the collective plots can be partly attributed to motives for insurance against production uncertainty. Production uncertainty cannot be directly observed. Nevertheless, given that the main production system in the study area is rain-fed crop cultivation, which strongly depends on rainfall, I use rainfall variability as a proxy for production uncertainty.

This part of the study provides the estimation results of plot-level labor allocation and crop yield performance across collective and individual plots taking into account rainfall variability represented by the coefficient of variation of rainfall from 1981 to 2007. The likelihood of the participation of the nuclear household in collective farming with extended family members depending on rainfall variability is also presented here.

1.8.1 Rainfall variability and labor allocation

The estimation results related to the hypothesis that higher labor allocation on the collective plots are partly driven by motives for risk insurance are presented in Table 1.7 (for total labor) and Table 1.8 (for male, female, and child labor). Three specifications are presented in each table: (1) only controls for the binary variable *Collective* and its interaction with the coefficient of variation of rainfall (2) adds plot characteristics, while (3) adds village covariates.[40] These results are obtained using the sample where collective and male individual plots coexist and correspond to the estimation of equation 7. All standard errors in these regressions are clustered at the village level. Rainfall variability has been standardized to ease the interpretation of the results –that is, such that the coefficient estimates on the interaction term are interpreted as an approximate percent increase in the amount of labor following an increase in rainfall variability by one standard deviation. The coefficient estimate of the interaction term is positive and statistically different from zero at the 5 percent significance level for total labor when all available covariates are included (Table 1.7, column 3). When labor is disaggregated, the magnitude of the coefficient is much larger for female labor with a statistical significance level of 5 percent, followed by male labor while there is no indication of any significant differences with respect to child labor.

[40] Rainfall variability cannot be included in the estimations without interacting it with the collective indicator, as this variable is constant within villages and between the two rounds of the panel. Rainfall variability is computed for crop cultivation season (May through September).

Table 1.7 Estimation of log of labor allocation (person-days/ha) across collective and male individual plots with rainfall variability (without plot covariates)

	Log(total labor/ha)		
	(1)	(2)	(3)
Collective	0.177***	0.391***	0.335***
	(0.036)	(0.041)	(0.055)
CV_rain*Collective	0.056	0.069*	0.079**
	(0.038)	(0.039)	(0.039)
Plot covariates?	No	Yes	Yes
Village covariates?	No	No	Yes
HHCYFE?	Yes	Yes	Yes
Observations	6,391	6,391	6,391
R-squared	0.028	0.104	0.107

Plot level observations. Robust clustered standard error at the village level in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Sample restricted to households within which collective and male individual plots coexist. All specifications include household-year-crop fixed effects. CV_rain=Rainfall variability and is computed for crop cultivation season (May through September) from 1981 to 2007. For ease of interpretation, CV_rain has been standardized. Fewer observations here relative to Table 1.4 because of missing village-level data for some villages. For ease of interpretation, CV_rain has been standardized. Top and bottom 1 percent of plot size and outcome variables dropped from sample. Plot covariates include log of plot size, use of organic fertilizer (1=yes), inorganic fertilizer (1=yes), plot tenure (=1 if owned by household), and soil type (clay, sandy, clay and sandy mix, or gravel). Village level covariates include outmigration (i.e., whether village experienced households moving out of village over the last ten years), access to formal credit in village, and village size (in terms of number of households in village)

Table 1.8 Estimation of log of labor allocation (person-days/ha) across collective and male individual plots controlling for rainfall (controlling for plot covariates)

	Panel A: Log(male labor/ha)			Panel B: Log(Female labor/ha)			Panel C: Log(Child labor/ha)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Collective	0.092**	0.305***	0.256***	0.341***	0.487***	0.501***	0.720***	0.817***	0.617***
	(0.040)	(0.049)	(0.064)	(0.061)	(0.068)	(0.099)	(0.070)	(0.084)	(0.124)
CV_rain*Collective	0.062	0.077*	0.087*	0.121**	0.129**	0.133**	-0.04	-0.041	-0.008
	(0.045)	(0.046)	(0.046)	(0.058)	(0.059)	(0.061)	(0.063)	(0.064)	(0.065)
Plot covariates?	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Village covariates?	No	No	Yes	No	No	Yes	No	No	Yes
HHCYFE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,391	6,391	6,391	6,391	6,391	6,391	6,391	6,391	6,391
R-squared	0.009	0.074	0.077	0.038	0.053	0.055	0.101	0.113	0.121

Plot level observations. Robust clustered standard error at the village level in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Sample restricted to households within which collective and male individual plots coexist. All specifications include household-year-crop fixed effects. CV_rain=Rainfall variability and is computed for crop cultivation season (May through September) from 1981 to 2007. For ease of interpretation, CV_rain has been standardized. Fewer observations here relative to Table 1.4 because of missing village-level data for some villages. Top and bottom 1 percent of plot size and outcome variables dropped from sample. Plot covariates include log of plot size, use of organic fertilizer (1=yes), inorganic fertilizer (1=yes), plot tenure (=1 if owned by household), and soil type (clay, sandy, clay and sandy mix, or gravel). Village level covariates include outmigration (i.e., whether village experienced households moving out of village over the last ten years), access to formal credit in village, and village size (in terms of number of households in village)

With the inclusion of the interaction term, the differential effect of a plot being collectively managed on labor allocation is now captured by the sum of the coefficient estimates of the interaction term and the *Collective* indicator –that is, $\hat{\gamma} + \hat{\kappa}$. Note that the standard deviation of the coefficient of variation (CV) is 0.005 (with a corresponding mean of 0.216), which is relatively low. Despite this low cross-sectional variation in rainfall variability across villages, I find significant differences in labor allocation by different levels of rainfall variability. For example, according to the results presented in Table 1.7 in column 2, an increase of one standard deviation in the CV of rainfall leads to an additional labor allocation gap across collective and individual plots by about 7 percent and this is statistically different than zero at the 10 percent significance level.

The corresponding figures for male and female labor are approximately 8 percent and 13 percent, respectively (Table 1.8, columns 2). These labor allocation gaps remain robust to the inclusion of village level covariates (Tables 1.7 and 1.8, columns 3), with larger coefficients and stronger statistical significance level, suggesting that estimates of κ are unlikely to be substantially biased by omitted village level characteristics.

Labor allocation is further disaggregated by grain and non-grain production in Table 1.9, Panel A and Panel B, respectively. There is a strong indication of different levels of correlation between rainfall variability and labor allocation across collective and individual plots by type of crop cultivation. Specifically, while the estimates of coefficients of the interaction term *CV_rain*Collective* are positive and significant for grain production, the corresponding figures for non-grain are not statistically different from zero. This holds regardless of whether plot or village covariates are included. Since grain production is the main source of livelihood in the study area, these findings provide strong supporting evidence of my claim that the higher labor allocation on the collective plots can be partly attributed to motives for securing food availability.

The differences in labor allocation are substantiated in the yield results presented in Table 1.10, where yield gap across collective and individual plots are higher among households living in areas with high rainfall variability. For example, considering the specification where all control variables are included (Table 1.10, column 3), households living in villages where the CV of rainfall variability is one standard deviation higher, achieve approximately 10 percent more crop yields on their collective plots relative to their individual plots.[41]

Table 1.9 Estimation of log of total labor allocation (person-days/ha) across collective and male individual plots controlling for rainfall by grain and non-grain production

VARIABLES	Panel A: Grain only			Panel B: Non-grain only		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Collective=1	0.135**	0.373***	0.311***	0.185***	0.403***	0.374***
	(0.060)	(0.061)	(0.095)	(0.039)	(0.057)	(0.070)
CV_rain*Collective	0.119**	0.123**	0.137**	0.01	0.008	0.017
	(0.058)	(0.056)	(0.056)	(0.039)	(0.042)	(0.042)
Plot covariates	No	Yes	Yes	No	Yes	Yes
Village covariates	No	No	Yes	No	No	Yes
HHYCFE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,794	3,794	3,794	2,598	2,598	2,598
R-squared	0.029	0.102	0.109	0.029	0.120	0.126

Plot level observations. Robust clustered standard error at the village level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to households within which collective and male individual plots coexist. All specifications include household-year-crop fixed effects. CV_rain=Rainfall variability and is computed for crop cultivation season (May through September) from 1981 to 2007. For ease of interpretation, CV_rain has been standardized. Top and bottom 1 percent of plot size and outcome variables dropped from sample. Plot covariates include log of plot size, use of organic fertilizer (1=yes), inorganic fertilizer (1=yes), plot tenure (=1 if owned by household), and soil type (clay, sandy, clay and sandy mix, or gravel). Village level covariates include outmigration (i.e., whether village experienced households moving out of village over the last ten years), access to formal credit in village, and village size (in terms of number of households in village)

Udry (1996) demonstrates that differences in crop yield resulting from differences in labor allocation across plots (male and female plots) of similar physical characteristics are evidence for efficiency loss due to decreasing marginal productivity of labor. Accordingly, while the current work does not test for efficiency, the fact that the labor allocation gap in Tables 1.7 and 1.8 is translated into a higher yield gap in Table 1.10 suggests efficiency loss among households in the study area.

[41] The results with the data disaggregated by grain and non-grain, not reported here, though positive, did not reveal any statistical significant difference.

Table 1.10 Estimation of the log of yield for all crops (FCFA/ha) across collective and male individual plots controlling for rainfall variability

	Log(yield (FCFA/ha))		
	(1)	(2)	(3)
Collective	0.080*	0.283***	0.188**
	(0.043)	(0.058)	(0.081)
CV_rain*Collective	0.074*	0.088**	0.097**
	(0.042)	(0.040)	(0.040)
Plot covariates?	No	Yes	Yes
Village covariates?	No	No	Yes
HHCYFE?	Yes	Yes	Yes
Observations	4,728	4,728	4,728
R-squared	0.013	0.061	0.066

Crop level observations. Robust clustered standard error at the village level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to households within which collective and male individual plots coexist. All specifications include household-year-crop fixed effects. CV_rain=Rainfall variability and is computed for crop cultivation season (May through September) from 1981 to 2007. For ease of interpretation, CV_rain has been standardized. Fewer observations in column (2) because of missing village-level data for some villages. Top and bottom 1 percent of plot size and outcome variables dropped from sample. Plot covariates include log of plot size, use of organic fertilizer (1=yes), inorganic fertilizer (1=yes), plot tenure (=1 if owned by household), and soil type (clay, sandy, clay and sandy mix, or gravel). Village level covariates include outmigration (whether village experienced households moving out of village over the last ten years), access to formal credit in village, and village size (in terms of number of households in village)

1.8.2 Rainfall variability and participation in collective farming

Based on the labor allocation results presented in Tables 1.7 and 1.8, it is sensible to hypothesize that collective farming may be viewed as an ex ante risk management strategy against production risk among households in the study zone, which I test by estimating equation 9. Specifically, I estimate a linear probability model where the outcome variable is a binary variable taking one if the household is engaged in collective farming, and zero otherwise. The results obtained from the estimation of equation 9 at the household level are presented in Table 1.11. Recall that the sample used here includes all the three types of households described in section 4. However, because of differences in norms that govern land distribution to female and male plot managers (see section 1.6 for more details), all female plots have been excluded from the sample before putting the data at the household level.[42]

[42] The results (available upon request) remain robust to the inclusion of female plots.

Table 1.11 Test for collective farming as ex-ante risk mitigation strategy. Dependent variable is participation of nuclear household in collective farming

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
Rainfall variability (standardized CV)	0.051***	0.055***	0.025***	0.051***	0.023***
	(0.007)	(0.008)	(0.005)	(0.008)	(0.005)
Head age 30-40 (<=30 omitted)		-0.088***			-0.036***
		(0.016)			(0.012)
Head age 40-50		-0.158***			-0.073***
		(0.020)			(0.015)
Head age 50-60		-0.084***			-0.031***
		(0.019)			(0.015)
Head age>60		-0.044**			-0.025
		(0.022)			(0.014)*
Household size		-0.024***			0.013***
		(0.003)			(0.002)
Land holding			-0.10***		-0.10***
			(0.004)		(0.004)
Draft animal=1			-0.091***		-0.091***
			(0.014)		(0.015)
Access to formal credit in village				-0.001	0.003
				(0.026)	(0.016)
Number of HHs in village				-0.000**	0
				0.000	0.000
Village experienced outmigration				-0.007	-0.02**
				(0.016)	(0.011)
Observations	5,325	5,325	5,325	5,325	5,325
R-squared	0.015	0.061	0.580	0.017	0.583

* $p<0.1$; ** $p<0.05$; *** $p<0.01$. Observations are at the household level. Clustered standard errors at the village level are in parentheses. Sample includes all restricted households (after dropping all female plots). Household covariates include size of nuclear household and its land holding. Village level covariates include outmigration (whether village experienced households moving out of village over the last ten years), access to formal credit in village, and village size (in terms of number of households in village). Rainfall variability is computed for crop cultivation season (May through September) from 1981 to 2007. For ease of interpretation, rainfall variability has been standardized.

The results, obtained with the first wave of the data are presented for five different specifications (Models 1-5).[43] The motivation for these alternative specifications is to check the consistency of the coefficient estimates of the key variable –that is rainfall variability. Model 1 represents the specification with rainfall variability only. Models 2 and 3 include controls for household demographics (represented

[43] I use only the first wave data because participation in collective farming does not vary much across the two waves. In addition, Historical rainfall variability is the same across the two waves, such that panel regressions with household fixed effect cannot be used. Results (not shown here) using the second wave of observations are consistent with the current findings.

by the size of the household and the head's age) and household asset holdings (captured by total land and possession of a draft animal), respectively. Model 4 controls for village covariates (availability of formal credit in the village, whether the village experienced outmigration of households over the last ten years, and the total number of households in the village) while Model 5 includes all covariates.

The results in Model 1 indicate that an increase of one standard deviation in the CV of rainfall is associated with a nuclear household being more likely to be engaged in collective farming by about 5 percentage point. Given that the standard deviation of the sample is only 0.005, this finding implies that the differential impact of rainfall variability would have been much higher, had there been more cross-sectional variation in rainfall variability.

One of the central arguments for collective farming is the benefit from the experience of the elderly household members in dealing with adverse weather conditions, which allows extended family members to mitigate their exposure to production variability (Rosenzweig and Wolpin, 1985). This argument is supported by the negative and highly statistically significance level of the coefficient estimates on the nuclear household head's age range. Particularly, with the omitted age category being 30-year-old or younger, the statistics in Model 2 show that nuclear households where the head's age is between 30 and 40 are about 9 percentage point less likely to be engaged in collective farming relative to their counterparts where the head's age is less than 30-year old. This statistic goes up to almost 16 percentage points when the head's age is between 40 and 50. The differential effect of the head's age range remains robust to the inclusion of all covariates (Model 5) but the coefficient estimates when the head's age is greater than 60, is only marginally statistically different from zero.

The results in Model 2 also show that larger nuclear households are less likely to be engaged in collective farming. This result is anticipated given that a larger number of individuals in the household represents more manpower and, hence, no need to rely on collective farming to satisfy labor requirement. The sign of the coefficient on household size is flipped in Model 5, when all available covariates are controlled for, which is puzzling, but the magnitude becomes very low (less than one percentage point).

With respect to assets holding, in Model 3, I find that nuclear household with larger land holdings are less likely to engage in collective farming. This evidence is consistent with finding from previous work in Burkina Faso (Kazianga and Wahhaj, 2017) where the authors evoke limited access to land markets as one of the driving factors for collective farming among extended family members. A similar case was observed in India (Rosenzweig and Wolpin, 1985). Model 3 also controls for draft animal ownership, which represents an important agricultural technology among subsistence farmers for land preparation. The size of the corresponding coefficient is almost 10 percent and statistically different from zero at the 1 percent significance level, implying that nuclear households who own a draft animal are much less likely to be engaged in collective farming. Since draft animal is an indivisible investment, the current finding strongly corroborates the view of economies of scale, in terms of technology adoption, as one of the driving factors for collective farming (Carter, 1987; Mathijs, E., & Swinnen, 2001).

Note how the size and the significance level of the coefficient on rainfall variability remains strongly consistent across the different specifications, except when asset holdings are included as controls where the size of the coefficient is reduced by about half.[44] Therefore, although the current results do not provide grant for causal inferences, they provide strong suggestive evidence that collective farming constitutes an ex-ante risk mitigation mechanism for households in the study area of the current work.

1.9 Conclusion and policy implications

This paper investigates household labor allocation and crop yield across collective and individual plots among rural households in the Segou region of Mali. There is strong empirical evidence that collective plots are more intensively farmed with labor, which translates into higher crop yield performance on collective plots by up to 47 and 46 percent, respectively.

I claim that the higher labor allocation and crop yields on collective plots are driven partly by the way collective farming may constitute an ex ante risk mitigation strategy among households in the study zone. This assertion is tested by using village level historical rainfall data to show that differences in labor

[44] The coefficient on rainfall variability is 0.054 when land holding and draft animal ownership are omitted in Model 5 (results not reported here).

allocation across collective and individual plots are higher among households in sites with greater rainfall variability.

The argument behind the view of collective farming as an ex ante risk mitigation strategy is that it enables nuclear households to lower their production variability. The study provides evidence in support of this claim by showing that yield dispersion across time is significantly lower on collective plots relative to individual plots. Furthermore, I show with strong suggestive evidence that places with higher rainfall variability tend to have a higher concentration of households engaged in collective farming with extended household members.

While the evidence of risk insurance presented here is compelling, it is important to be mindful that this analysis does not provide a basis for causal inference. Ex ante risk insurance motives are surely not the only potential driving factors behind the observed labor allocation gap. Other plausible factors include social and cultural norms regarding moral obligations to contribute to joint family welfare, which may compel nuclear household members to provide more labor on collective plots.[45]

Despite these limitations, the findings provide novel and noteworthy implications for the study of the complexity of household economic decision-making in sub-Saharan African countries. A striking feature is that the results from the current study, while in line with empirical evidence in Burkina Faso by Kazianga and Wahhaj (2013) –that is, higher intensity of labor use on collective plots relative to individual plots – differ from the findings of Guirkinger and Platteau (2014) among rural households in Mali.

Rather than perceiving the current results as conflicting with those obtained by Guirkinger and Platteau (2014), I consider the two studies to be complementary due to the regional disparities between

[45] This is particularly important in the context of Malian culture, where there is social pressure to contribute to the joint welfare of the whole family, and failing to do so may result in being perceived as selfish (personal communications and observations). Individuals who detract from following such social norms are usually the subject of gossip, which can tarnish their reputation and social status. Nevertheless, it is less plausible that social norms constitute an important factor in explaining the higher labor allocation on the collective plots. In fact, Guirkinger and Platteau (2014), whose work is in another region in the same country, report that some heads of households complain about shrinking behaviors exhibited by individual plot managers on the collective plots.

the two study zones. To be specific, the study area of the current work is mainly characterized by drylands, with very limited access to irrigation, where the main source of livelihood is rain-fed crop cultivation. Untimely execution of farming activities can have dire impacts on crop yield performance. This may provide incentives for nuclear households in the region to scrupulously work on the collective plots, where it is possible for them to have “brute strength” and “experienced” labor, as well as a larger pool of labor supply, allowing them to insure one another against production risk. In contrast, individuals in the study zone of Guirkinger and Platteau (2014), especially the Sikasso region, have more opportunities to engage in the cultivation of cash crops on their individual plots, as well as to access non-agricultural income generating opportunities.[46]

The finding that differences in plot-level intra-household labor allocation are reflected in crop yield performance across plots of similar characteristics in the current work is consistent with previous empirical evidence in West Africa. This strongly supports the premise that labor remains a major productive factor among households in this region. As a result, if motives for ex ante risk insurance are plausible driving factors in the observed labor allocation gaps among households in the current work, increasing farmers’ access to productive safety nets and promoting labor saving technologies presents a strong potential to alleviate labor bottleneck at the peak of the farming season and improve overall agricultural productivity. For example, herbicide use, which significantly reduces weeding efforts while increasing crop yield performance, is very low among the studied population despite recent findings of a steep rise in herbicides use in other regions in Mali.[47]

The differences in the empirical literature regarding rural household economies highlighted here,

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[46] Indeed, the authors find that “mixed farming” –that is, the coexistence of collective and individual plots within the same household –is more predominant among extended households with a higher proportion of bottomland relative to extended households without individual plots. This supports the argument of the opportunity for more cash crop production for “individualized farming” in that study region. In effect, bottomland is not only suited for crops production such as vegetables, but also can be exploited beyond the main cropping season (Guirkinger et al., 2015) when there is less competition in labor demand across individual and collective plots, as the latter tend to be mainly grown to rain-fed crops.

[47] Haggblade et al. (2017) find that up to 60 percent of plots in the Sudanian Savana zone in Mali receive herbicide while the corresponding figure in the current work is only about 5 percent . This sharp difference is likely to be due to regional disparities in terms of agro-ecological zones and herbicide markets.

underline the challenge faced by development practitioners in West Africa to improve aggregate measures of household welfare in contexts where intra-household dynamics can be location-specific. It is therefore often difficult to tailor policies to specific groups of people or locations. This highlights the need for continuous research efforts in understanding household production decision making in these regions.

APPENDICES

APPENDIX A ADDITIONAL DESCRIPTIVE STATISTICS

Table 1A. 1 Plot characteristics and crop choice across collective and individual plots (Full sample)

	Individual Plots (N=9,889)		Collective Plots (N=41,059)		
	Mean	SD	Mean	SD	P-value
Female=1	0.710	0.450	-	-	0.000
Plot size	0.600	1.020	2.090	2.700	0.000
Clay soil	0.370	0.480	0.350	0.480	0.029
Clay & sandy mix	0.350	0.480	0.370	0.480	0.022
Sandy Soil	0.260	0.440	0.260	0.440	0.903
Gravel	0.020	0.150	0.030	0.160	0.355
Household owns plot	0.940	0.240	0.980	0.140	0.000
Household rents plots	0.060	0.240	0.020	0.140	0.000
Millet	0.160	0.370	0.270	0.450	0.000
Sorghum	0.090	0.290	0.190	0.390	0.000
Maize	0.030	0.180	0.100	0.300	0.000
Rice	0.040	0.200	0.090	0.290	0.000
Peanut	0.530	0.500	0.140	0.340	0.000
Beans	0.030	0.180	0.030	0.170	0.062
Chickpeas	0.040	0.190	0.050	0.220	0.002
Fonio	0.010	0.100	0.080	0.270	0.000
Sesame	0.050	0.230	0.040	0.200	0.000
Inorganic fertilizer=1	0.110	0.320	0.300	0.460	0.000
Organic fertilizer=1	0.230	0.420	0.320	0.470	-
Total labor (person-days/ha)	158.090	473.740	132.800	189.390	0.001
Male labor (person-days/ha)	37.760	136.920	62.040	88.350	0.000
Female labor (person-days/ha)	88.210	316.530	35.270	70.230	0.000
Child labor (person-days/ha)	32.540	122.180	35.650	66.280	0.106

Plot level observations. Sample includes all households as well as all plots (including female individual plots)

Table 1A. 2 Plot characteristics and crop choice across all collective and male individual plots

	Individual Plots (N=2,595)		Collective Plots (N=35,802)		
VARIABLES	Mean	SD	Mean	SD	P-value of Diff.
Plot size	0.86	0.92	2.15	2.68	0.00

Table 1A.2 (cont'd)

Soil type					
Clay soil	0.32	0.47	0.35	0.48	0.03
Clay & sandy mix	0.37	0.48	0.36	0.48	0.01
Sandy soil	0.27	0.45	0.26	0.44	0.75
Gravel	0.03	0.17	0.03	0.16	0.83
Household owns plot	0.96	0.2	0.98	0.15	0.00
Main source of water is rain	0.98	0.13	0.97	0.17	0.11
Crop choice					
Millet	0.14	0.35	0.28	0.45	0.00
Sorghum	0.10	0.30	0.19	0.4	0.00
Maize	0.06	0.23	0.1	0.3	0.00
Rice	0.06	0.23	0.09	0.29	0.00
Peanut	0.47	0.5	0.14	0.34	0.00
Beans	0.04	0.2	0.03	0.16	0.73
Chickpeas	0.02	0.15	0.05	0.22	0.00
Fonio	0.03	0.17	0.08	0.27	0.00
Sesame	0.09	0.28	0.04	0.19	0.00
Inorganic fertilizer (1=yes)	0.11	0.32	0.31	0.46	0.00
Organic fertilizer (1=yes)	0.26	0.44	0.33	0.47	0.00
Inorganic fertilizer (kg/ha)	7.06	29.31	15.65	53.49	0.00
Total labor (person-days/ha)	106.86	97.14	109.83	94.67	0.59
Male labor (person-days/ha)	56.1	55.79	52.95	47.22	0.03
Female labor (person-days/ha)	26.77	35.91	28.48	32.39	0.13
Child labor (person-days/ha)	24.14	35.34	28.45	33.73	0.01

Plot level observations. Sample includes all households participating in collective farming after dropping all female plots

Table 1A. 3 Plot characteristics by crop choice across collective and male individual plots

	Individual plots			Collective plots			
	N	Mean	SD	N	Mean	SD	P-value of diff.
Clay_rice	83	0.88	0.33	450	0.89	0.31	0.83
Clay_millet	249	0.22	0.42	1,471	0.23	0.42	0.75
Clay_sorghum	178	0.47	0.5	1,024	0.43	0.5	0.29
Clay_maize	104	0.38	0.49	545	0.34	0.47	0.39

Table 1A.3 (cont'd)

Clay_fonio	61	0.13	0.34	479	0.18	0.38	0.28
Clay_sesame	145	0.29	0.46	257	0.31	0.46	0.72
Clay_peanut	793	0.27	0.45	591	0.28	0.45	0.76
Clay_beans	50	0.18	0.39	145	0.39	0.49	0.00
Clay_chickpeas	40	0.1	0.3	232	0.19	0.39	0.11
Clay_sandy_rice	83	0.05	0.22	450	0.07	0.25	0.42
Clay_sandy_millet	249	0.42	0.49	1,471	0.41	0.49	0.71
Clay_sandy_sorghum	178	0.39	0.49	1,024	0.35	0.48	0.40
Clay_sandy_maize	104	0.36	0.48	545	0.38	0.49	0.59
Clay_sandy_fonio	61	0.49	0.5	479	0.32	0.47	0.00
Clay_sandy_sesame	145	0.45	0.5	257	0.34	0.47	0.04
Clay_sandy_peanut	793	0.38	0.48	591	0.33	0.47	0.03
Clay_sandy_beans	50	0.38	0.49	145	0.32	0.47	0.46
Clay_sandy_chickpeas	40	0.42	0.5	232	0.31	0.47	0.19
Sandy_rice	83	0.05	0.22	450	0.02	0.15	0.35
Sandy_millet	249	0.33	0.47	1,471	0.34	0.47	0.85
Sandy_sorghum	178	0.13	0.34	1,024	0.18	0.38	0.08
Sandy_maize	104	0.18	0.39	545	0.25	0.43	0.13
Sandy_fonio	61	0.33	0.47	479	0.45	0.5	0.02
Sandy_sesame	145	0.2	0.4	257	0.26	0.44	0.21
Sandy_peanut	793	0.32	0.47	591	0.35	0.48	0.23
Sandy_beans	50	0.42	0.5	145	0.26	0.44	0.04
Sandy_chickpeas	40	0.42	0.5	232	0.48	0.5	0.54
Gravel_rice	83	0.02	0.15	450	0.02	0.13	0.75
Gravel_millet	249	0.02	0.15	1,471	0.02	0.15	0.81
Gravel_sorghum	178	0.01	0.11	1,024	0.04	0.19	0.01
Gravel_maize	104	0.08	0.27	545	0.03	0.16	0.10
Gravel_fonio	61	0.05	0.22	479	0.05	0.22	0.92
Gravel_sesame	145	0.06	0.24	257	0.1	0.3	0.15
Gravel_peanut	793	0.03	0.17	591	0.04	0.19	0.29
Gravel_beans	50	0.02	0.14	145	0.03	0.16	0.76
Gravel_chickpeas	40	0.05	0.22	232	0.02	0.15	0.43

Plot level observations. Sample includes all households after dropping all female plots

Table 1A.4. Coefficients of correlation between rainfall variability and village covariates

Village covariates	**Correlation coefficient with rainfall variability**
Households in village have access to formal credit in village	0.081
Village size (number of households in village)	-0.03
Village experienced outmigration of households over last 10 years	0.004

APPENDIX B ROBUSTNESS CHECK BY DROPPING ALL FERTILIZED PLOTS

Table 1B.1 Log of labor allocation estimation after dropping all plots with inorganic and organic fertilizer

VARIABLES	Total labor	Male labor	Female labor	Child labor
Collective=1	0.415***	0.319***	0.474***	0.829***
	(0.049)	(0.054)	(0.079)	(0.099)
Log of plot size	-0.296***	-0.300***	-0.204***	-0.149**
	(0.033)	(0.037)	(0.057)	(0.063)
Household owns plot=1	0.188	-0.015	0.322	0.952***
	(0.227)	(0.227)	(0.327)	(0.327)
Clay and sandy soil (clay is omitted)	-0.032	-0.04	-0.22	0.111
	(0.086)	(0.084)	(0.143)	(0.166)
Sandy	-0.147**	-0.088	-0.257**	-0.059
	(0.071)	(0.075)	(0.118)	(0.136)
Gravel	0.131	-0.063	0.245	0.439
	(0.145)	(0.153)	(0.278)	(0.328)
Observations	4,141	4,141	4,141	4,141
R-squared	0.1338	0.0965	0.061	0.1325

Plot level observations. Robust clustered standard error at the household level in parentheses.
* *p*<0.1; ** *p*<0.05; *** *p*<0.01. Sample restricted to households within which collective and male individual plots coexist. All plots on which organic and or inorganic fertilizer is used are dropped. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample

Table 1B.2 Log of crop yield (FCFA/ha) estimation after dropping all plots with inorganic and organic fertilizer

VARIABLES	All crops	Cereal crops	Non-cereal crops
Collective=1	0.255***	0.383**	0.273***
	(0.065)	(0.164)	(0.071)
Log of plot size	-0.213***	-0.109	-0.310***
	(0.066)	(0.116)	(0.082)
Household owns plot=1	0.064	0.383**	0.103
	(0.298)	(0.164)	(0.313)
Clay and sandy soil (clay is omitted)	-0.082	0.732***	-0.266**
	(0.126)	(0.219)	(0.126)
Sandy	-0.349***	0.054	-0.415***
	(0.110)	(0.333)	(0.117)
Gravel	0.011	0.148	-0.085

Table 1B.2 (cont'd)

	(0.237)	(0.354)	(0.268)
Observations	3,009	1,062	1,947
R-squared	0.0641	0.1623	0.093

Crop level observations. Robust clustered standard error at the household level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to households within which collective and male individual plots coexist. All plots on which organic and or inorganic fertilizer is used are dropped. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample. FCFA: Franc Communauté Financière Africaine. The exchange rate at the survey times was approximately $1US=500 FCFA

APPENDIX C GENDER BIAS IN LABOR ALLOCATION AND CROP YIELD

Table 1C. 1 Log of labor allocation estimation across collective and all individual plots (including female plots)

VARIABLES	Total labor	Male labor	Female labor	Child labor
Collective=1	0.521***	0.410***	0.698***	0.951***
	(0.031)	(0.040)	(0.054)	(0.058)
Female plot manager=1	-0.03	-1.917***	1.303***	-0.280***
	(0.032)	(0.052)	(0.060)	(0.062)
Log of plot size	-0.384***	-0.257***	-0.389***	-0.232***
	(0.012)	(0.020)	(0.017)	(0.022)
Organic fertilizer=1	0.159***	0.147***	0.101***	0.167***
	(0.018)	(0.026)	(0.028)	(0.032)
Inorganic fertilizer==1	0.041**	0.063**	0.069**	0.044
	(0.021)	(0.031)	(0.032)	(0.039)
Household owns plot=1	0.055	0.177**	0.025	0.15
	(0.058)	(0.081)	(0.084)	(0.103)
Clay and sandy soil (clay is omitted)	0.129***	0.071*	0.115***	0.200***
	(0.028)	(0.042)	(0.040)	(0.051)
Sandy	-0.001	-0.044	-0.016	0.021
	(0.024)	(0.037)	(0.037)	(0.049)
Gravel	-0.007	-0.128*	0.04	0.084
	(0.057)	(0.068)	(0.086)	(0.102)
Observations	46,358	46,358	46,358	46,358
R-squared	0.1718	0.4467	0.2581	0.1229

Plot level observations. Robust clustered standard error at the household level in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Sample restricted to households within which collective, male, and female plots coexist. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample

Table 1C. 2 Log of crop yield (FCFA/ha) estimation across collective plots and all individual plots (including female plots)

VARIABLES	All crops	Cereal crops	Non-cereal crops
Collective=1	0.341***	0.549***	0.338***
	(0.047)	(0.090)	(0.057)
Female plot manager=1	-0.391***	-0.684***	-0.317***
	(0.049)	(0.087)	(0.059)
Log of plot size	-0.158***	-0.231***	-0.283***
	(0.027)	(0.044)	(0.043)
Organic fertilizer=1	0.308***	0.371***	0.155
	(0.060)	(0.068)	(0.100)
Inorganic fertilizer==1	0.169***	0.145*	0.047
	(0.063)	(0.075)	(0.105)
Household owns plot=1	-0.049	-0.007	-0.009
	(0.085)	(0.169)	(0.093)
Clay and sandy soil (clay is omitted)	0.013	0.002	0.007
	(0.057)	(0.080)	(0.074)
Sandy	-0.012	0.015	-0.038
	(0.054)	(0.097)	(0.063)
Gravel	-0.059	-0.02	-0.136
	(0.165)	(0.233)	(0.208)
Observations	31,410	18,349	13,061
R-squared	0.1199	0.2662	0.0861

Crop level observations. Robust clustered standard error at the household level in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Sample restricted to households within which collective, male and female individual plots coexist. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample. FCFA: Franc Communauté Financière Africaine. The exchange rate at the survey times was approximately $1US=500 FCFA

APPENDIX D LABOR HETEROGENEITY BY PLOT MANAGEMENT STRUCTURE

Labor heterogeneity estimation results (from equation 3) using the sample restricted to households within which collective and male individual plots coexist are presented in Tables 1D.1 and 1D.2. Since the key variable is Collective, results are presented when only that variable is included (Table 1D.1) before adding the other plot covariates (Table 1D.2). In addition, results are presented separately for all crops, and grain and non-grain crops.

There is strong evidence that collective plots are more likely to receive more heterogeneous labor relative to individual plots regardless of whether plot covariates are omitted or included, though the magnitude of the coefficients are relatively smaller when more controls are added. The results disaggregated by crop type reveal that grain crops are more likely to receive all combination of labor compared to non-grain crops, which is consistent with the descriptive statistics in section 1.5. This suggests that collective farming is practiced to secure the availability of these crops. Since grain crops constitute the major source of livelihood for these households, the results hint that the latter engage in collective farming to guarantee food security among themselves.[48]

[48] These results can be extended to the perception that labor heterogeneity allows to achieve higher crop yield performance. However, the empirical examination of this perception is beyond the scope of this paper.

Table 1D. 1 Linear probability results of labor heterogeneity across collective and individual plots (without plot covariates)

	All crops			Grain crops			Non-grain crops		
VARIABLES	All sources	Male and female	Male and child	All sources	Male and female	Male and child	All sources	Male and female	Male and child
			x						
Collective=1	0.221***	0.075***	0.206***	0.234***	0.126***	0.201***	0.211***	0.037**	0.209***
	-0.021	-0.015	-0.02	-0.03	-0.023	-0.029	-0.026	-0.018	-0.024
HHCYFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,907	6,907	6,907	4,106	4,106	4,106	2,801	2,801	2,801
R-squared	0.111	0.023	0.110	0.125	0.055	0.111	0.101	0.006	0.110

Plot level observations. Robust clustered standard error at the plot level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to households within which collective and male individual plots coexist. All plots receive male labor because these plots are all managed by male farmers. Top and bottom 1 percent of plot size dropped from sample

Table 1D. 2 Linear probability results of labor heterogeneity across collective and individual plots (controlling for plot covariates)

	All crops			Grain crops			Non-grain crops		
VARIABLES	All sources	Male and female	Male and child	All sources	Male and female	Male and child	All sources	Male and female	Male and child
Collective=1	0.167***	0.042**	0.167***	0.182***	0.106***	0.159***	0.135***	-0.011	0.156***
	(0.024)	(0.018)	(0.023)	(0.034)	(0.026)	(0.033)	(0.034)	(0.026)	(0.032)
Log of plot size	0.053***	0.035***	0.037***	0.042***	0.016	0.033**	0.087***	0.068***	0.055*
	(0.014)	(0.012)	(0.013)	(0.015)	(0.014)	(0.014)	(0.032)	(0.024)	(0.029)
Organic fertilizer=1	-0.029	-0.004	-0.01	-0.011	-0.007	0.009	-0.102*	0.013	-0.096*
	(0.018)	(0.015)	(0.017)	(0.017)	(0.015)	(0.017)	(0.061)	(0.050)	(0.053)
Inorganic fertilizer==1	0.017	0.019	0.019	0.011	0.009	0.009	0.047	0.029	0.083
	(0.023)	(0.020)	(0.022)	(0.021)	(0.019)	(0.020)	(0.077)	(0.061)	(0.072)
Household owns plot=1	0.069	-0.044	0.111	-0.014	-0.034	0.056	0.164	-0.049	0.177
	(0.073)	(0.060)	(0.071)	(0.077)	(0.078)	(0.078)	(0.123)	(0.081)	(0.114)
Clay & sandy soil (clay is omitted)	0.018	-0.002	0.014	-0.013	0.004	-0.026	0.061	-0.008	0.069
	(0.031)	(0.024)	(0.028)	(0.031)	(0.027)	(0.025)	(0.061)	(0.045)	(0.057)
Sandy	0.018	0.014	-0.007	0.015	0.005	-0.017	0.025	0.03	0.01

Table 1D.2 (cont'd)

	(0.026)	(0.022)	(0.025)	(0.026)	(0.024)	(0.024)	(0.053)	(0.041)	(0.051)
Gravel	0.019	0.023	-0.009	-0.029	-0.04	0.018	0.083	0.125	-0.072
	(0.052)	(0.047)	(0.059)	(0.052)	(0.049)	(0.042)	(0.093)	(0.083)	(0.122)
HHCYFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,907	6,907	6,907	4,106	4,106	4,106	2,801	2,801	2,801
R-squared	0.124	0.034	0.120	0.138	0.060	0.122	0.123	0.030	0.129

Plot level observations. Robust clustered standard error at the plot level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to households within which collective and male individual plots coexist. All plots receive male labor because these plots are all managed by male farmers. Top and bottom 1 percent of plot size dropped from sample

APPENDIX E ROBUSTNESS CHECK USING DECILES OF PLOT SIZE

Table 1E. 1 Log of labor allocation estimation across collective and individual plots using plot deciles

VARIABLES	Total labor	Male labor	Female labor	Child labor
collective	0.401***	0.323***	0.498***	0.798***
	(0.039)	(0.043)	(0.063)	(0.080)
2.surface_decile	-0.213***	-0.239***	0.02	0.007
	(0.066)	(0.075)	(0.129)	(0.128)
4.surface_decile	-0.465***	-0.510***	-0.188	-0.213
	(0.070)	(0.080)	(0.132)	(0.136)
6.surface_decile	-0.627***	-0.722***	-0.270*	-0.304*
	(0.086)	(0.096)	(0.160)	(0.167)
7.surface_decile	-0.679***	-0.706***	-0.429***	-0.251*
	(0.078)	(0.089)	(0.148)	(0.151)
8.surface_decile	-0.753***	-0.789***	-0.430***	-0.323**
	(0.079)	(0.092)	(0.149)	(0.158)
9.surface_decile	-0.746***	-0.784***	-0.406**	-0.281
	(0.089)	(0.100)	(0.157)	(0.178)
10.surface_decile	-0.835***	-0.826***	-0.514***	-0.404**
	(0.091)	(0.106)	(0.166)	(0.175)
Organic fertilizer=1	0.094***	0.116***	0.015	0.052
	(0.036)	(0.040)	(0.058)	(0.062)
Inorganic fertilizer==1	0.007	-0.009	0.122*	0.039
	(0.041)	(0.045)	(0.073)	(0.075)
Household owns plot=1	0.124	0.076	-0.157	0.477**
	(0.143)	(0.142)	(0.228)	(0.225)
Clay and sandy soil (clay is omitted)	0.068	0.037	-0.011	0.202**
	(0.054)	(0.053)	(0.098)	(0.102)
Sandy	-0.068	-0.027	-0.127	-0.041
	(0.050)	(0.053)	(0.082)	(0.087)
Gravel	0.035	-0.026	-0.063	0.299
	(0.115)	(0.109)	(0.177)	(0.185)
Observations	6,897	6,897	6,897	6,897
R-squared	0.116	0.092	0.053	0.115

Plot level observations. Robust clustered standard error at the household level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to households within which collective and male individual plots coexist. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample

Table 1E. 2 Log of crop yield estimation across collective and individual plots using plot deciles

VARIABLES	All crops	Cereal crops	Non-cereal crops
collective	0.308***	0.355***	0.326***
	(0.055)	(0.093)	(0.068)
2.surface_decile	-0.148	-0.541***	-0.05
	(0.097)	(0.204)	(0.104)
4.surface_decile	-0.325***	-0.433**	-0.348***
	(0.108)	(0.207)	(0.124)
6.surface_decile	-0.351*	-0.753***	-0.196
	(0.205)	(0.245)	(0.295)
7.surface_decile	-0.552***	-0.394	-0.746***
	(0.156)	(0.288)	(0.171)
8.surface_decile	-0.516***	-0.513***	-0.667***
	(0.166)	(0.192)	(0.247)
9.surface_decile	-0.631***	-0.627***	-1.160***
	(0.169)	(0.229)	(0.317)
10.surface_decile	-0.687***	-0.800***	-1.081***
	(0.176)	(0.240)	(0.373)
Organic fertilizer=1	0.238**	0.357***	0.165
	(0.108)	(0.134)	(0.166)
Inorganic fertilizer==1	0.034	-0.042	-0.08
	(0.107)	(0.129)	(0.189)
Household owns plot=1	0.136	0.044	0.166
	(0.188)	(0.208)	(0.268)
Clay and sandy soil (clay is omitted)	-0.099	0.299*	-0.306***
	(0.094)	(0.160)	(0.112)
Sandy	-0.264***	-0.211	-0.321***
	(0.091)	(0.173)	(0.107)
Gravel	-0.055	-0.426	-0.12
	(0.173)	(0.282)	(0.255)
Observations	5,062	2,824	2,238
R-squared	0.0651	0.1326	0.1173

Crop level observations. Robust clustered standard error at the household level in parentheses. * *p*<0.1; ** *p*<0.05; *** *p*<0.01. Sample restricted to households within which collective and male individual plots coexist. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample. FCFA: Franc Communauté Financière Africaine. The exchange rate at the survey times was approximately $1US=500 FCFA. Fewer number of observations relative to Table 1E.1 because yield variables are at the crop-level

APPENDIX F ROBUSTNESS CHECK WITH OVERLAPPING PLOT SIZE

Table 1F. 1 Log of labor allocation estimation across plots with overlapping plot size

VARIABLES	Total labor	Male labor	Female labor	Child labor
Collective=1	0.380***	0.293***	0.485***	0.791***
	(0.039)	(0.044)	(0.063)	(0.081)
Log of plot size	-0.256***	-0.260***	-0.175***	-0.133***
	(0.024)	(0.027)	(0.042)	(0.046)
Organic fertilizer=1	0.117***	0.138***	0.044	0.055
	(0.037)	(0.040)	(0.056)	(0.063)
Inorganic fertilizer==1	-0.008	-0.02	0.098	0.017
	(0.042)	(0.044)	(0.075)	(0.078)
Household owns plot=1	0.096	0.052	-0.188	0.457**
	(0.139)	(0.138)	(0.226)	(0.228)
Clay and sandy soil (clay is omitted)	0.088	0.063	-0.012	0.206*
	(0.055)	(0.055)	(0.099)	(0.107)
Sandy	-0.082	-0.034	-0.180**	-0.041
	(0.052)	(0.056)	(0.084)	(0.090)
Gravel	0.045	-0.014	-0.072	0.31
	(0.120)	(0.113)	(0.184)	(0.195)
Observations	6,699	6,699	6,699	6,699
R-squared	0.1064	0.0796	0.0507	0.1138

Plot level observations. Robust clustered standard error at the household level in parentheses. * *p*<0.1; ** *p*<0.05; *** *p*<0.01. Sample restricted to households within which collective and male individual plots coexist and plots with overlapping plot size. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample.

Table 1F. 2 Log of crop yield (FCFA/ha) estimation across plots with overlapping plot size

VARIABLES	All crops	Cereal crops	Non-cereal crops
Collective=1	0.309***	0.387***	0.310***
	(0.057)	(0.101)	(0.071)
Log of plot size	-0.220***	-0.181**	-0.309***
	(0.052)	(0.071)	(0.079)
Organic fertilizer=1	0.232**	0.282**	0.175
	(0.115)	(0.128)	(0.185)
Inorganic fertilizer==1	-0.008	-0.08	-0.05
	(0.109)	(0.125)	(0.206)
Household owns plot=1	0.102	0.018	0.164
	(0.197)	(0.196)	(0.263)

Table 1F.2 (cont'd)

Clay and sandy soil			
(clay is omitted)	-0.112	0.287*	-0.303***
	(0.097)	(0.167)	(0.115)
Sandy	-0.251***	-0.257	-0.293***
	(0.094)	(0.203)	(0.108)
Gravel	0.024	-0.247	0.111
	(0.166)	(0.314)	(0.232)
Observations	4,890	2,688	2,202
R-squared	0.0644	0.1021	0.0842

Crop level observations. Robust clustered standard error at the household level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to households within which collective and male individual plots coexist and plots with overlapping plot size. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample. FCFA: Franc Communauté Financière Africaine. The exchange rate at the survey times was approximately $1US=500 FCFA. Fewer number of observations relative to Table 1F.1 because yield variables are at the crop-level

APPENDIX G ROBUSTNESS CHECK BY DROPPING PLOTS WITH COMPANION CROPS

Table 1G. Log of labor allocation estimation after dropping all plots with companion crops

VARIABLES	Total labor	Male labor	Female labor	Child labor
Collective=1	0.343***	0.277***	0.388***	0.733***
	(0.046)	(0.052)	(0.079)	(0.097)
Log of plot size	-0.281***	-0.301***	-0.166***	-0.115*
	(0.034)	(0.037)	(0.054)	(0.059)
Organic fertilizer=1	0.147**	0.192***	-0.007	0.07
	(0.059)	(0.062)	(0.095)	(0.104)
Inorganic fertilizer==1	0.036	-0.021	0.239**	0.05
	(0.065)	(0.068)	(0.107)	(0.126)
Household owns plot=1	0.117	0.075	-0.292	0.600**
	(0.172)	(0.175)	(0.267)	(0.268)
Clay and sandy soil (clay is omitted)	0.121	0.072	0.002	0.308**
	(0.077)	(0.077)	(0.141)	(0.149)
Sandy	-0.052	-0.04	-0.104	-0.002
	(0.067)	(0.072)	(0.120)	(0.117)
Gravel	0.082	0.01	0.188	0.22
	(0.166)	(0.163)	(0.283)	(0.251)
Observations	4,906	4,906	4,906	4,906
R-squared	0.1087	0.1022	0.0397	0.1107

Plot level observations. Robust clustered standard error at the household level in parentheses. * $p<0.1$; ** $p<0.05$; *** $p<0.01$. Sample restricted to households within which collective and male individual plots coexist. All plots with companion crops are dropped. All specifications include household-year-crop fixed effects. Top and bottom 1 percent of plot size and outcome variables dropped from sample.

APPENDIX H ESTIMATION OF THE LOG OF CROP YIELD ACROSS COLLECTIVE AND HEADS' INDIVIDUAL PLOTS

Table 1H. Estimation of the log of crop yield (FCFA/ha) across collective and heads' individual plot using PMYFE

	Panel A: All crops			Panel B: Grain crops			Panel C: Non-grain crops		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Collective=1	0.258***	0.249***	0.253***	0.357***	0.331***	0.329***	0.253**	0.268***	0.268***
	(0.08)	(0.07)	(0.07)	(0.12)	(0.12)	(0.12)	(0.10)	(0.10)	(0.10)
Log of plot size	-0.212***	-0.228***	-0.231***	-0.197***	-0.211***	-0.207***	-0.374***	-0.380***	-0.384***
	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)	(0.10)	(0.10)	(0.10)
Organic fertilizer=1		0.116	0.112		0.097	0.095		0.245	0.255
		(0.08)	(0.08)		(0.08)	(0.08)		(0.20)	(0.21)
Inorganic fertilizer==1		0.157*	0.155*		0.234**	0.234**		-0.014	0.001
		(0.09)	(0.09)		(0.11)	(0.11)		(0.23)	(0.23)
Household owns plot=1		-0.244	-0.238		0.252**	0.195		-0.451	-0.412
		(0.29)	(0.30)		(0.12)	(0.17)		(0.39)	(0.37)
Clay and sandy soil (clay is omitted)			0.096			0.098			-0.02
			(0.08)			(0.11)			(0.18)
Sandy			0.095			0.02			0.164
			(0.10)			(0.15)			(0.17)
Gravel			0.046			-0.257			0.192
			(0.16)			(0.23)			(0.28)
PMFE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Crop FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1352	1352	1352	766	766	766	586	586	586
R-squared	0.239	0.246	0.247	0.133	0.150	0.154	0.425	0.429	0.432
Sample Mean (SD)	(Mean=11.735; SD=1.080)			(Mean=11.605; SD=.926)			(Mean=11.904; SD=1.233)		

Crop level observations. Robust clustered standard error at the household level in parentheses. * p<0.1; ** p<0.05; *** p<0.01. Sample restricted to heads that control simultaneously their own individual plots and collective plots. Top and bottom 1 percent of plot size and outcome variables dropped from sample. Village level prices recorded through community questionnaires were used to convert production into monetary value FCFA: Franc Communauté Financière Africaine. The exchange rate at the survey times was approximately $1US=500 FCFA.

APPENDIX I YIELD DISPERSION ACROSS COLLECTIVE AND INDIVIDUAL PLOTS

A major underpinning argument in favor of collective farming as an ex ante risk mitigation strategy is that it reduces the nuclear household's exposure to production uncertainty. As a result, crop yield performance should be less variable on collective plots relative to individual plots. Since the data used in this study are from two rounds, to empirically test this assertion, I regress the residuals obtained from the household-crop-year fixed effects estimation –that is, the crop yield performance across collective and individual plots presented in Table 1I –on the time indicator. The central idea is that, if production is less variable on collective plots, then the yield dispersion across the two survey rounds for group of the collective plots should be smaller relative to that of the individual plots.

Table 1I. Yield variability across collective and male individual plots

	(1)	(2)
VARIABLES	Group 1: Collective=0	Group 2: Collective=1
Year=2012	-0.479***	-0.181***
	(0.056)	(0.032)
Plot covariates	Yes	Yes
Crop FE	Yes	Yes
Household FE	No	No
Observations	1,304	3,758
R-squared	0.3074	0.2085
chi2(1) = 26.10	26.10	26.10
Probability > chi2 = 0.0000		

Sample restricted to households within which collective and male individual plots coexist. Residuals are obtained from yield estimation across collective and individual plots (originally presented in Table 1.XX).

The results presented in Table 1I, show that the size of the coefficient of the year indicator for individual plots is more than 2.5 times larger relative to the coefficient for the group of collective plots (Table 1I, Column 2).

A Chow test, which tests whether the coefficients vary between the two groups indicates that this difference is different from zero at the 1 percent statistical significance level with a corresponding chi2 of one degree. This finding provides strong suggestive evidence that, collective farming does indeed allow households to mitigate production variability across time. These findings are consistent with results from previous work that find less variability in agricultural profit across times among intergenerational households relative to households without elderly members (Rosenzweig and Wolpin, 1985).

REFERENCES

REFERENCES

Adams, W., & Mortimore, M. (1997). Agricultural Intensification and Flexibility in the Nigerian Sahel. The Geographical Journal, 163(2), 150-160.

Beaman, L. and Dillon, A. (2012). Do household definitions matter in survey design? Results from a randomized survey experiment in Mali. Journal of Development Economics, 98(1), pp.124-135.

Bharadwaj, P. (2015). Fertility and rural labor market inefficiencies: Evidence from India. Journal of development Economics, 115, 217-232.

Barrett, C. B., Moser, C. M., McHugh, O. V., & Barison, J. (2004). Better technology, better plots, or better farmers? Identifying changes in productivity and risk among Malagasy rice farmers. American Journal of Agricultural Economics, 86(4), 869-888.

Barrett, C. B., Sherlund, S. M., & Adesina, A. A. (2008). Shadow wages, allocative inefficiency, and labor supply in smallholder agriculture. Agricultural Economics, 38(1), 21-34.

Becker, L. (1996). Access to labor in rural Mali. Human Organization, 55(3), 279-288.

Benjamin, D. (1992). Household composition, labor markets, and labor demand: testing for separation in agricultural household models. Econometrica: Journal of the Econometric Society, 287-322.

Binswanger, H. P., & Deininger, K. (1997). Explaining agricultural and agrarian policies in developing countries. Journal of Economic Literature, 35(4), 1958-2005.

Boserup, E. (1970). Women's role in economic development.

Browning, M., & Chiappori, P. A. (1998). Efficient intra-household allocations: A general characterization and empirical tests. Econometrica, 1241-1278.

Burton, M. L., & White, D. R. (1984). Sexual division of labor in agriculture. American Anthropologist, 86(3), 568-583.

Carter, M. R. (1984). Resource allocation and use under collective rights and labour management in Peruvian coastal agriculture. The Economic Journal, 94(376), 826-846.

Carter, M. R. (1987). Risk sharing and incentives in the decollectivization of agriculture. Oxford Economic Papers, 39(3), 577-595.

Cooper, P. J. M., Dimes, J., Rao, K. P. C., Shapiro, B., Shiferaw, B., & Twomlow, S. (2008). Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: An essential first step in adapting to future climate change? Agriculture, Ecosystems & Environment, 126(1), 24-35.

Deininger, K. (1995). Collective agricultural production: A solution for transition economies? World Development, 23(8), 1317-1334.

Dillon, B., & Barrett, C. B. (2017). Agricultural factor markets in Sub-Saharan Africa: an updated view with formal tests for market failure. *Food Policy*, *67*, 64-77.

Dillon, A., Mueller, V., & Salau, S. (2011). Migratory responses to agricultural risk in northern Nigeria. American Journal of Agricultural Economics, 93(4), 1048-1061.

Fafchamps, M. (1993). Sequential labor decisions under uncertainty: An estimable household model of West-African farmers. Econometrica: Journal of the Econometric Society, 1173-1197.

Feng, S., Heerink, N., Ruben, R., & Qu, F. (2010). Land rental market, off-farm employment and agricultural production in Southeast China: A plot-level case study. China Economic Review, 21(4), 598-606.

Foltz, J. D. (2004). Credit market access and profitability in Tunisian agriculture. Agricultural Economics, 30(3), 229-240.

Food and Agriculture Organization (2006). Country Pasture/Forage Resource Profiles

http://www.fao.org/ag/agp/agpc/doc/counprof/Mali/mal.

Foster, A. D., & Rosenzweig, M. R. (1994). A test for moral hazard in the labor market: Contractual arrangements, effort, and health. The Review of Economics and Statistics, 213-227.

Gebremedhin, Berhanu, and Scott M. Swinton. "Investment in soil conservation in northern Ethiopia: the role of land tenure security and public programs." Agricultural Economics 29, no. 1 (2003): 69-84.

Gianessi, L. P. (2013). The increasing importance of herbicides in worldwide crop production. Pest management science, 69(10), 1099-1105.

Goldstein, M., & Udry, C. (2008). The profits of power: Land rights and agricultural investment in Ghana. Journal of Political Economy, 116(6), 981-1022.

Guirkinger, C., & Platteau, J. P. (2014). The effect of land scarcity on farm structure: empirical evidence from Mali. Economic Development and Cultural Change, 62(2), 195-238.

Guirkinger, C., Platteau, J. P., & Goetghebuer, T. (2015). Productive inefficiency in extended agricultural households: Evidence from Mali. Journal of Development Economics, 116, 17-27.

Haggblade, S., Minten, B., Pray, C., Reardon, T., & Zilberman, D. (2017). The Herbicide Revolution in Developing Countries: Patterns, Causes, and Implications. The European Journal of Development Research, 1-27.

Haggblade, S., Smale, M., Theriault, V., & Assima, A. (2017). Causes and consequences of increasing herbicide use in Mali. The European Journal of Development Research, 1-27.

Hayes, J., Roth, M., & Zepeda, L. (1997). Tenure security, investment and productivity in Gambian agriculture: A generalized probit analysis. American Journal of Agricultural Economics, 79(2), 369-382.

Israelsen, L. D. (1980). Collectives, communes, and incentives. Journal of Comparative Economics, 4(2), 99-124.

Jack, B. K. (2013). Market inefficiencies and the adoption of agricultural technologies in developing countries.

Kazianga, H., & Wahhaj, Z. (2013). Gender, Social Norms, and Household Production in Burkina Faso. Economic Development and Cultural Change, 61(3), 539-576.

Kazianga, H., Wahhaj, Z., 2016. Intra-household Resource Allocation and Familial Ties. Oxford CSAE Working Paper WPS 2016-06.

Kazianga, H., & Wahhaj, Z. (2017). Intra-household resource allocation and familial ties. Journal of Development Economics, 127, 109-132.

Lamb, R. L. (2003). Inverse productivity: Land quality, labor markets, and measurement error. Journal of Development Economics, 71(1), 71-95.

Lee, D. R., Barrett, C. B., & McPeak, J. G. (2006). Policy, technology, and management strategies for achieving sustainable agricultural intensification. Agricultural economics, 34(2), 123-127.

Lin, J. Y. (1987). Household Farm, Cooperative Farm, and Efficiency: Evidence from Rural De-collectivization in China. Economic Growth Center, Yale University.

McMillan, J., Whalley, J., & Jing, Z. L. (1987). Incentive effects of price rises and payment-system changes on Chinese agricultural productivity growth.

Meyer, C. A. (1989). Agrarian reform in the Dominican Republic: An associative solution to the collective/individual dilemma. World Development, 17(8), 1255-1267.

Mathijs, E., & Swinnen, J. F. (2001). Production organization and efficiency during transition: An empirical analysis of East German agriculture. The Review of Economics and Statistics, 83(1), 100-107.

Mishra, A., Hansen, J. W., Dingkuhn, M., Baron, C., Traoré, S. B., Ndiaye, O., & Ward, M. N. (2008). Sorghum yield prediction from seasonal rainfall forecasts in Burkina Faso. Agricultural and forest meteorology, 148(11), 1798-1814.

Moser, C. M., & Barrett, C. B. (2003). The disappointing adoption dynamics of a yield-increasing, low external-input technology: the case of SRI in Madagascar. Agricultural Systems, 76(3), 1085-1100.

Ondersteijn, C. J. M., Giesen, G. W. J., & Huirne, R. B. M. (2003). Identification of farmer characteristics and farm strategies explaining changes in environmental management and environmental and economic performance of dairy farms. Agricultural Systems, 78(1), 31-55.

Putterman, L., & DiGiorgio, M. (1985). Choice and efficiency in a model of democratic semi-collective agriculture. Oxford Economic Papers, 37(1), 1-21.

Qaim, M., Subramanian, A., Naik, G., & Zilberman, D. (2006). Adoption of Bt cotton and impact variability: Insights from India. Applied Economic Perspectives and Policy, 28(1), 48-58.

Quisumbing, A. R. (1996). Male-female differences in agricultural productivity: Methodological issues and empirical evidence. World Development, 24(10), 1579-1595.

Quisumbing, A. R., & Pandolfelli, L. (2010). Promising approaches to address the needs of poor female farmers: Resources, constraints, and interventions. World Development, 38(4), 581-592.

Ricker-Gilbert, J., Jumbe, C., & Chamberlin, J. (2014). How does population density influence agricultural intensification and productivity? Evidence from Malawi. Food Policy, 48, 114-128.

Rosenzweig, M. R., & Wolpin, K. I. (1985). Specific experience, household structure, and intergenerational transfers: farm family land and labor arrangements in developing countries. The Quarterly Journal of Economics, 961-987.

Shorr, N. (2000). Early utilization of flood-recession soils as a response to the intensification of fishing and upland agriculture: Resource-use dynamics in a large Tikuna community. Human Ecology, 28(1), 73-107.

Smale, M., Byerlee, D., & Jayne, T. (2013). Maize revolutions in sub-Saharan Africa. In an African green revolution (pp. 165-195). Springer Netherlands.

Steiner, K. G. (1998). Using farmers' knowledge of soils in making research results more relevant to field practice: experiences from Rwanda. Agriculture, ecosystems & environment, 69(3), 191-200.

Stone, M., Stone, G., & Robert McC. Netting. (1995). The Sexual Division of Labor in Kofyar Agriculture. American Ethnologist, 22(1), 165-186. Retrieved from http://www.jstor.org/stable/646051.

Sultan, B., Baron, C., Dingkuhn, M., Sarr, B., & Janicot, S. (2005). Agricultural impacts of large-scale variability of the West African monsoon. Agricultural and forest meteorology, 128(1), 93-110.

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. Journal of Agricultural Economics, 64(3), 597-623.

Theriault, V., Smale, M., & Haider, H. (2017). How Does Gender Affect Sustainable Intensification of Cereal Production in the West African Sahel? Evidence from Burkina Faso. World Development, 92, 177-191.

Udry, C. 1996. "Gender, Agricultural Production, and the Theory of the Household." Journal of Political Economy, 104(5), 1010-1046.

Udry, C., Hoddinott, J., Alderman, H., & Haddad, L. (1995). Gender differentials in farm productivity: implications for household efficiency and agricultural policy. Food Policy, 20(5), 407-423.

USAID. (2010). Mali Land Tenure Assessment Report.

http://fsg.afre.msu.edu/promisam_2/references/ARD_2010_Mali_Land_Tenure_Assessment.pdf.

USAID (2008). Plan de Sécurité Alimentaire Commune Urbaine de Ségou 2008-2012, Commissariat à la Sécurité Alimentaire, République du Mali, USAID-Mali, 2008.

World Bank (2016). Country Overview, Mali. http://www.worldbank.org/en/country/mali/overview.

World Bank (2014). LSMS-ISA-Mali.

World Culture Encyclopedia. http://www.everyculture.com/Ja-Ma/Mali.html.

2 HOUSEHOLD STRUCTURE INFLUENCES LABOR ALLOCATION DECISIONS DUE TO AGRICULTURAL TECHNOLOGY ADOPTION: EVIDENCE FROM BURKINA FASO

2.1 Introduction

Food security has become more tenuous over recent decades because of a combination of worsening soil fertility and reduced arable land per capita from rising population. Because of these pressures, farmers must rely on agricultural intensification to ensure sustainable food security (Lele and Stone, 1989; Garnett et al., 2013). Several programs have been implemented to promote the adoption of agricultural technologies among farmers (e.g., fertilizer and improved seed subsidies). However, though some progress has been observed in some regions, especially with the "early green revolution" in Latin America and Asia (Evenson and Gollin, 2003), low adoption rates of such technologies tend to persist among subsistence farmers, especially in sub-Saharan Africa.

This has fueled numerous studies to investigate the determinants of agricultural technology adoption among farmers (Just and Zilberman, 1983; Foster and Rosenzweig, 1995; Moser and Barrett, 2003; Croppenstedt et al., 2003; Barrett et al., 2004; Moreno and Sunding, 2005; Langyintuo and Mungoma, 2008; Gine and Young, 2009; Duflo and Kremer, 2011; Kijima et al., 2011; Noltze et al., 2012; Jack, 2013; Khonje et al., 2015; among others). Much of the empirical research has found strong evidence that the household endowment in labor is a major contributing factor (Croppenstedt et al., 2003; Moser and Barrett, 2003; Barrett et al., 2004), especially for labor intensive technologies (e.g., cite some of the technologies). This highlights the importance of investigating how households respond in terms of their labor allocation to the introduction of a new labor-intensive agricultural technology, especially in a setting where incomplete or missing labor markets are prevalent.

In this article, we investigate household labor response to the introduction of a fertilizer application technique called microdosing among rural subsistence farmers in Burkina Faso. The microdosing technique directly targets the seed-hole and requires much less fertilizer compared to broadcasting methods. This makes it less financially constraining and a climate-smart technology

(Resnick et al., 2012; Aune and Coulibaly, 2015). When applied properly, it has the potential to increase yield by more than 20 percent relative to the broadcasting technique. But the downside is its intensive labor requirements (ICRISAT, 2012). These features of microdosing, especially its labor-intensive nature, make it suitable for exploring how household labor allocation is affected by programs encouraging agricultural intensification.

We first investigate the household labor response by the household's endowment in land. Household land holding, which is a proxy for wealth, has been proven to be an important determinant of agricultural technology adoption (Just and Zilberman, 1983; Foster and Rosenzweig, 1985; Moreno and Sunding, 2005; Langyintuo and Mungoma, 2008; Khonje et al., 2015). Larger land holders are likely to test a new technology using a portion of their land, while small land holders may be skeptical to adopt an unproven technology, especially, if it is to be applied to the production of a crop that constitutes their main source of livelihood (Langyintuo et al., 2008).

In ruling out differential treatment effects of microdosing by landholdings, we focus on how labor allocation responds to the introduction of the technology depending on the structure of the household (nuclear vs. extended family households).

Why is it important to investigate the differential impact of the microdosing program by household structure? First, with increasing fragmentation of households to smaller units in the developing world, mixed household structures – that is, the coexistence of nuclear family households and extended family households – are predominant in in many sub-Saharan African countries (Bongaarts 2001 and West, 2010).

Second, the majority of the households in these regions face missing or imperfect labor markets, (De Janvry et al., 1991; Barrett et al., 2004) and therefore heavily rely on family members as the main source of their agricultural labor (Udry, 1996; Doss, 2006; Marenya and Barrett, 2007; Morton, 2007; Kazianga and Wahhaj, 2013).

Third, we expect differences in production organization systems between nuclear and extended family households would lead to differences in labor response to the introduction of microdosing.

Extended households, comprised of multiple nuclear families, differ from nuclear households in that they have more adult labor available to them. Yet, given their larger size, labor allocation decisions among extended households could inhibit adoption if coordination problems create high transaction costs compared to nuclear households (Poteete and Ostrom, 2004). Furthermore, extended family members simultaneously manage private plots owned by nuclear family members and collective plots, which are owned by all extended family members. Private plot managers are required to provide labor on the collective plots before working on their own plots (Becker, 1996; Kazianga and Wahhaj, 2013, Guirkinger and Platteau, 2014, Guirkinger et al., 2015).

We address potential endogeneity in the decision to adopt microdosing by exogenously varying the availability of this technology.[49] To do so, we implemented a Randomized Control Trial (RCT) where the treatment included training in the microdosing application technique, along with a starter kit comprised of certified sorghum seed and fertilizer. We then estimate the Intention To Treat (ITT) effects with Difference-in-Difference (DID) applied to pre- and post- program intervention data.

Our findings provide evidence of a differential impact of the microdosing program by household structure, and no indication of any heterogeneous impact by land holding. Specifically, with the sample restricted to the bottom three quintiles of baseline total landholding, we find that total labor allocated to sorghum production increased by approximately 16 percent among nuclear households assigned to treatment (about 15 person-days per hectare), whereas the corresponding figure for extended households was a reduction of about 29 percent (approximately 33 person-days per hectare).

We attribute the heterogeneous impact of the microdosing by household structure to three factors. First, we show that the increased labor requirement for fertilizer application induced by the microdosing intervention led extended households to substitute labor away from other sorghum production activities, while there is no indication of any substitutions effects of labor among the nuclear households. Second,

[49] For example, household characteristics such as wealth and household composition may determine technology adoption (Croppenstedt et al., 2003; Teklewold et al., 2013). Other endogenous determinants of technology adoption include productivity differences across households (McMillan, 1987; Doss, 2001, Mendola, 2008; Foster and Rosenzweig, 2010).

we argue that the program provided higher incentives for nuclear households to exert more effort in their sorghum production because they are the sole claimants of the potential accrued production. Finally, we present suggestive evidence that differences in resource control is a likely contributing source to the differential impact of the program across nuclear and extended households.

These findings have important implications for agricultural development policy interventions in developing countries with heterogeneity in household structures –where some households are formed by nuclear family members while others are composed by extended family members. Our study also highlights the need for a better understanding of how households may differ in their agricultural production organization, depending on household composition. Doing so would enable policy makers to design more inclusive agricultural development intervention programs and, consequently, for increased overall agricultural productivity.

The remainder of the paper is structured as follows. We present the conceptual framework where we describe our experimental design, the microdosing technology as well as how we classify households according to nuclear or extended categories. In Section 3, we describe the difference-in-difference methods used to identify the intent to treat effect of the microdosing technology intervention. Section 4 provides a description of the data and sample restrictions. We also summarize differences in demographic and production characteristics across nuclear and extended households, as well as balancing tests by treatment assignment within each household category. Section 6 presents concludes the paper.

2.2 Conceptual framework

2.2.1 Experimental Design

The current work is part of a larger program implemented in Burkina Faso, with the objective to increase food security among rural households. For these households as well as many rural households in the West African Sahel, sorghum is the main food staple and most widely cultivated dryland crop. Yet, as in much of this region, average sorghum yields in Burkina Faso are estimated at 0.8 tons per hectare, despite the potential to attain over 2 tons per hectare (Ministry of Agriculture, Burkina Faso 2010). The specific objective of the program was therefore to improve sorghum yields through the promotion of a particular application technique of mineral fertilizer, called microdosing. The microdosing technique directly targets the plant by applying small quantities (about 2 grams) of fertilizer in or near the seed hole during sowing time, or as top dressing 3 to 4 weeks after the seeded crop begins to emerge. This technique lowers the required amount of fertilizer per hectare by more than 50 percent (ICRISAT, Fertilizer Microdosing, January 2012), making it less financially constraining relative to standard fertilizer application techniques. In the case of hard soil, farmers dig small holes and fill them with manure before the rain begins. Once the rain starts, the fertilizer and seeds are placed into the moist soil. This technique captures the water, so that it does not run off the hard-crusted soil, thereby encouraging root growth (ICRISAT, January 2009).

When applied to the seeding of improved sorghum varieties, microdosing raises yields considerably. In Burkina Faso, INERA (Institut de l'Environnement et de Recherches Agricoles) has reported grain yields of nearly 2000 kg/ha for improved sorghum varieties. Because the microdosing technique is climate-smart while lowering adoption barriers due to financial constraints, it has been perceived as one of the promising ways to sustainably increase agricultural productivity (Montpellier Panel Report, 2013, Aune and Coulibaly, 2015). Conversely, the primary drawbacks to microdosing are that it is time-consuming, laborious, and it is difficult to ensure that the correct amount of fertilizer is used for each dose.

Our experimental design used an encouragement scheme to randomly assign microdosing training and a starter kit, which included fertilizer and certified sorghum seed sufficient for one half hectare of sorghum production. We worked with AGRODIA, an organization of local agro-dealers in Burkina Faso, to supply these micro packets. The seed was certified by INERA, the public agricultural research institution in the country. INERA also provided training in microdosing to all households in treated villages.

We selected three provinces for the study: Bam and Sanmatenga from the Center-North region and Passoré from the North region. These provinces were selected because there is a high prevalence of sorghum cultivation and little cultivation of cash crops such as cotton. We collected a complete list of all

925 villages in these three provinces. Because this study was part of a larger project which involved collecting social network censuses in many of the villages, we restricted our potential pool of villages to those that were not too large to conduct such censuses. We therefore kept villages where the population size was between 190 and 800, provided that the number of households was no greater than 120 households. The number of households per village varied between 70 and 120 households. From the remaining 226 villages, 80 villages were randomly selected for the treatment group studied here, and 20 villages were randomly selected for the control group. In all these villages, a village enumeration included questions about plot information, sorghum production, and adoption of improved seeds.

Using this village enumeration, in each village we then randomly sampled approximately 30 households growing sorghum. For these households, we conducted baseline and follow-up household surveys, where we collected detailed production and socio-economic information. Thus, detailed household surveys were conducted for 2400 households in all 80 villages in the treatment group, and for 600 households in all 20 villages in the control group.

In each of 80 treated villages, approximately 15 of the 30 surveyed households were randomly selected to receive free micro-packets of certified sorghum seed and fertilizer.[50] In the current analysis, we compare these treated households to the households surveyed in control villages which did not receive any micro-packets or any training in micro-dosing. We exclude all households in treatment villages who did not receive free micro-packets but may have received training in microdosing. We do so to eliminate any potential spillover effects due to possible technological transfer, which in turn may lead to underestimation of the program's impact on treated households.

Finally, we do not impose compliance in our analysis as we are not able to capture actual take-up rates of the practices of the microdosing technique. This is because many households consider other existing fertilization techniques as microdosing. More importantly, self-declared take-up rates is more likely to be inflated in the control villages relative to the treatment villages, given that the treatment

[50] INERA reported that one village did not receive the intervention due difficulties in accessing the village. That village has been dropped from the sample.

certainly increased knowledge of microdosing practice in the treatment villages. Though we are not able to ensure clear differences in microdosing adoption among control and treatment groups, we are able to observe whether the pattern of self-declared take-up rates are similar across treatment and control groups by household structure as shown in Table 2A (see APPENDIX A)

2.2.2 Household Structure

We define a household as "a socio-economic unit within which one or more members, related or not, live in the same house or concession, pool their resources, and jointly meet the bulk of their food and other basic needs under the authority of one of them, called the head of household" (Beaman and Dillon, 2012). This definition of the household may include multiple "nuclear" households cohabiting in one "extended" household. Such cohabitation of multiple nuclear households may arise through two possible channels: vertical extension of the household, where married sons and their nuclear families have common residency with their fathers; and horizontal extension, where married brothers and their respective nuclear families cohabitate (Laslett and Wall 1982; West 2010; Kazianga and Wahhaj 2017).

Therefore, we define an "extended" household as a household that meets at least one of the following criteria: households having one married male who is not the household head; or household heads having married sons, married brothers, daughters-in-law, or sisters-in-law living in the household (Table 1, Panel A). Households that do not meet these criteria are classified as "nuclear" households. According to this definition, 354 of the 1,059 households in our final sample (about 33 percent) are extended households, and the remaining households are classified as nuclear households.

The leading criterion for being qualified as an extended household is the household having more than one married male. This condition is met by about 29 percent of the final sample. When classified by relationship to the head, approximately 16 percent of the heads have at least one married son and nearly 8 percent of them live with one or multiple married brothers. The father and married son relationship is mirrored by approximately 16 percent of heads having at least one daughter-in-law. However, while only about 9 percent of the heads cohabitate with married brothers, up to 13 percent of them have at least one sister-in-law (Table 2.1, Panel A).

Table 2.1 Sample Restrictions and Household Structure

Sample restrictions	**Number excluded**	**Number remaining**
All households in baseline	0	1,522
All households in follow-up	0	1,428
Households in both surveys	102	1,420
Remaining male-headed HHs	133	1,287
Remaining male-headed HHs with at least one plot managed by male	32	1,255
Remaining male-headed HHs producing sorghum at baseline	73	1,182
Remaining male-headed HHs producing sorghum both at baseline and follow-up	94	1,098
Final sample after dropping outliers and missing values	39	1,059
Household structure	**Number of Households**	
	Panel A: Final full sample	Panel B: Final Restricted sample
HH has at least one additional married male besides the head	311	157
HH head has at least one married son	170	84
HH head has at least one married brother	89	43
HH head has at least one daughter-in-law	162	73
HH head has at least one sister-in-law	133	64
Extended HHs (HHs that meet at least one of the criteria above)	354	181
Nuclear HHs (HHs that meet none of the criteria above)	705	496
Total number of HHs	**1,059**	**677**

Note: Observations are at the household level
Outliers identified as observations with values more than three times the standard deviation above the mean
Sorghum plot is identified as a plot on which sorghum is the main crop
Restricted sample is for households in the first three quintiles of land holding

Based on these criteria for the household structure classifications, extended household are certainly different from nuclear households in terms of their demographic characteristics and their landholding, as they are more likely to have larger landholding relative to the latter. In addition, given their larger size, they are more likely to have a larger pool of labor but may also face some coordination costs in productive factors allocation.

Finally, the microdosing intervention may generate different levels of incentives in terms of effort allocated to sorghum production depending on household structure since output produced in the extended households is shared amongst all extended family members. Precisely, nuclear households will be more motivated to exert higher efforts in their sorghum production following the reception of the microdosing kits because they get to keep all the marginal production that will originate from their marginal effort. Conversely in the extended households, the sharing rule is based on need, rather than on effort.[51] Based on these factors, our main research question is: How does labor allocation respond differently across households with differing family structure? To answer this question, we use the following general equation:

$$Y_i = \alpha + \beta_1 Househol\_structure + \boldsymbol{\beta_2 X_i} + \epsilon_{\mathrm{i}} \qquad (2.1)$$

where Y_i is the labor allocation response to the introduction of the microdosing technology, *Household_structure* is an indicator variable that takes 1 if an extended household and 0 otherwise, and $\boldsymbol{X_i}$ is a vector of household and production characteristics. The key coefficient in equation (1) is β_1. Our main prediction is that β_1 is different from zero. In other words, the microdosing intervention will have heterogeneous effects across nuclear and extended households.

2.3 Identification Strategy

Our randomized study design enables us to evaluate the impact of the program by applying Difference-in-Difference (DID) methods to identify the Intent to Treat (ITT) effect of being given training in microdosing and free packets of seed and fertilizer. Because technology adoption and household characteristics may be simultaneously determined (McMillan, 1987; Doss, 2001, Mendola, 2008; Foster and Rosenzweig, 2010), the randomization design permits identification of the direction of causality. The ITT approach compares outcomes between households assigned to treatment to those in the control villages without taking compliance into account. We use this approach instead of investigating the impact of the actual application of the microdosing technique because some households, especially those in the

[51] This claim stems from the assumption that the microdosing kit will be applied on collective plots in some of the extended households. Production from the collective plots is considered as a public good within these households (Kazianga and Wahhaj, 2013).

control villages, may inaccurately consider prior existing fertilization techniques, such as zai as microdosing.

As we are interested in the differential effects of the intervention depending on household endowment in land and on whether households are comprised of either extended or nuclear family structures (as outlined above), we carry out two distinct identification strategies. In the first, we interact treatment assignment (T_j) with baseline total land holding (L_{hj}^0), with households indexed by *h* and villages indexed by *j*. Therefore, we estimate OLS for the following set of regressions:

$$(Y_{hj}^1 - Y_{hj}^0) =$$

$$\beta_1 T_j + \beta_2 L_{hj}^0 + \beta_3(T_j \text{ x } L_{hj}^0) + \beta_4 E_{hj} + \beta_5 LShare_{hj}^0 + \mu_k + (\varepsilon_{hj}^1 - \varepsilon_{hj}^0), \tag{2.2}$$

where we difference outcome measures across pre- and post- treatment surveys. Superscripts 1 and 0 refer to follow-up and baseline data respectively. Equation (2) enables us to obtain DID estimators for β_1 and β_3 because it estimates changes in outcomes between baseline and follow-up values across assigned and control households. All outcome variables are measured per unit of land to account for potential economies of scale across different landholdings. Our primary outcomes are labor allocation in person-days per hectare in total and disaggregated by tasks, including the following: plowing, planting, inorganic and organic fertilizer application, weeding, and harvesting. Since treatment assignment is allocated by village, we cluster all standard errors by village. In this specification, we also control for household structure (E_{hj}), a binary variable that takes 1 if an extended household and 0 otherwise.

To identify household structure differential impacts, we carry out a second identification strategy where baseline total land holding is replaced with household structure. We interact treatment assignment (T_j) with the indicator variable for household structure (E_{hj}) and apply OLS estimation to the set of regressions defined as

$$(Y_{hj}^1 - Y_{hj}^0) =$$

$$\beta_1 T_j + \beta_2 E_{hj} + \beta_3(T_j \text{ x } E_{hj}) + \beta_4 L_{hj}^0 + \beta_5 LShare_{hj}^0 + \mu_k + (\varepsilon_{hj}^1 - \varepsilon_{hj}^0), \tag{2.3}$$

where we also control for baseline total land holding (L_{hj}^0).

In both specifications (2) and (3), we control for the share of total cultivated land devoted to sorghum as the main crop at baseline ($LShare_{hj}^0$) and commune fixed effects (μ_k).[52]

Finally, we remain mindful of the fact that nuclear and extended households differ from one another in a variety of ways. Not only are extended households comprised of more family members, they also have significantly larger land holdings. As a result, we rule out that differential estimates in ITT in specification (3) are due to differences in land holding at baseline by restricting our sample to households in the lower three quintiles of land holdings at baseline. We do so because a disproportionately higher number of extended households compared to nuclear households have land holdings in the top two quintiles. For this restricted sample, we find that average land holdings at baseline are similar for both nuclear and extended households (see Table 3.2). Sample means tests for this restricted sample also indicate that extended and nuclear households are relatively similar in terms of baseline fertilizer use rates, whether sorghum or maize is the main crop at baseline, and total sorghum production at baseline. Note that for the wider sample, extended and nuclear households differ along all of these dimensions (see Table 2.2).

2.4 Data

We collected detailed household survey data within our study villages, both before and after the intervention. We surveyed all those who received starter kits in treatment villages. In addition, we surveyed approximately 30 households at random from each of the control villages. The baseline survey took place in late 2013 and early 2014. Households received microdosing training and starter kits at the starting of the 2014-2015 agricultural campaign, and the follow-up survey was conducted one year later – in late 2014 and early 2015. Our multi-topic household survey collected information on various demographic, socio-economic, and agricultural production characteristics. We collected data at the

[52] Ideally, we would include village fixed effect but this is not feasible given that treatment assignment does not vary within village. This is because we dropped all households that are not assigned to treatment in treatment the villages to avoid spillovers, which may lead to underestimating the impact of the intervention.

household level as well as at the individual plot manager level. In total, we collected 1,529 household surveys at baseline. With a household attrition rate of 6.7 percent, we collected household surveys both at baseline and follow-up for 1,426 households.

2.4.1 Sample Restrictions

As our primary interest is to determine the differential impact of the microdosing intervention by household structure, and since male and female headed households are considerably different from one another, we first restrict our sample to male-headed households. Extended households are mostly headed by men (Colson 1962; Kazianga and Wahhaj 2015), and most female headed households are nuclear households. This restriction ensures that in comparing across different household structures, we are not conflating these differences with differences in male or female headed households. This drops about 10 percent of the households.

In addition, to eliminate any potentially differentiated effects specific to gender differences, we also exclude all female-controlled plots from the sample. Preliminary analysis of the sample (results not presented here) indicated that the proportion of female-plot managers among extended households is much higher relative to nuclear households. Consequently, comparing labor allocation across the two types of households without eliminating female-controlled plots will likely lead to outcomes being driven by gender-specific effects rather than by differences in household structure.

Given that our identification strategy consists of investigating changes in labor allocation to sorghum production across the pre- and post- treatment periods, the sample is further restricted to male-headed households that had at least one male-controlled sorghum plot in each of the two rounds, resulting in 1,098 remaining households.

Moreover, we identified outliers in labor allocation measured in person-days per hectare as those observations with values greater than three times the standard deviation. This restriction eliminates 39 households from our sample, resulting in a final full sample size of 1,059 households.

Finally, since the treatment targeted small sorghum growers and given that extended households tend to have larger land holdings, there is a concern that any findings on differential impact by household structure would be driven by differences in land holding. We address this concern by carrying out a final sample restriction where land holding is balanced across household structures. Specifically, we restrict the sample to the lower three quintiles of land holding, leading to a final sample size of 677 households of which about 27 percent are extended family households. Table 2.1 summarizes these sequential sample restrictions.

2.4.2 Demographic and Production Characteristics by Household Structure

Tables 2.2 and 2.3 present summary statistics of demographic and production characteristics for extended and nuclear households prior to our intervention. The two types of households are very different in terms of their demographic and production characteristics. First, the heads of extended households are on average about six years older than nuclear heads. As expected, the numbers of adult males and females are significantly higher for extended households.

These differences in household composition will likely impact their labor response to the introduction of the microdosing technology. In particular, the larger number of adults in the extended households implies the need for more coordination efforts in their labor allocation decisions. As labor markets are almost nonexistent in the study zone, households rely heavily on family labor for their agricultural production activities (Udry 1996; Kazianga and Wahhaj 2013). Therefore, since the microdosing technology is potentially labor-intensive, households may have to readjust their labor allocation if they were already facing labor constraints before the intervention. This possible need for labor allocation readjustment is likely to be higher for extended households relative to nuclear households.

Table 2.2 Demographic Characteristics Across Extended and Nuclear Households (Full sample)

	Nuclear HHs (N=705)		Extended HHs (N=354)		
VARIABLES	Mean	SD	Mean	SD	P-Value
Household is Assigned Treatment	0.66	0.48	0.65	0.48	0.94
Head Age	46.24	14.08	52.10	15.41	0.00
Number of Adult Males	1.90	1.13	3.61	1.79	0.00
Number of Adult Females	2.18	1.27	4.15	2.23	0.00
Household size (members older than 15 years)	4.51	1.88	8.12	3.45	0.00

Note: Observations at the household level

Table 2.3 Production Characteristics Across Extended and Nuclear Households (Full sample)

	Nuclear HHs (N=705)		Extended HHs (N=354)		
VARIABLES	Mean	SD	Mean	SD	P-Value
Household Uses Fertilizer	0.39	0.49	0.48	0.50	0.01
Intensity of fertilizer (kg/ha)	8.95	20.40	9.86	15.97	0.42
Total Land Holding (ha)	3.85	2.50	5.66	4.10	0.00
Total land where sorghum is main crop (ha)	2.97	2.14	4.40	3.61	0.00
Total land where millet is main crop (ha)	0.71	1.24	0.94	1.41	0.00
Total land where maize is main crop (ha)	0.05	0.22	0.09	0.32	0.02
Total land where rice is main crop (ha)	0.01	0.11	0.09	1.10	0.32
Total land where peanut is main crop (ha)	0.04	0.21	0.03	0.19	0.72
Labor Allocation to Plowing (person-days/ha)	9.779	9.924	11.34	11.91	0.05
Labor Allocation to Planting (person-days/ha)	13.62	10.55	15.64	10.75	0.00
Labor Allocation to Fertilizer Application (person-days/ha)	2.390	4.451	3.259	5.169	0.01
Labor Allocation to Manure Application (person-days/ha)	4.651	5.963	5.714	7.206	0.02
Labor Allocation to Weeding (person-days/ha)	37.44	37.66	40.16	31.67	0.21
Labor Allocation to Harvest (person-days/ha)	14.85	13.88	17.72	14.15	0.00
Total Labor Allocation (person-days/ha)	82.80	60.20	93.88	57.73	0.00
Total sorghum production	1,513	1,288	2,144	1,877	0.000
Total sorghum yield (kg/ha)	630.3	546.2	583.8	477.3	0.11

Note: Observations are at the household level

The larger household size of the extended household (in terms of adult members who are more than 14 years old) is further reflected in larger total land holdings devoted to agricultural production, especially for sorghum. Moreover, the proportion of households that apply fertilizer among extended households exceeds that of nuclear households by 9 percent, and the difference is statistically significant at 5 percent. However, there is no statistically significant difference in the intensity of fertilizer application. Relative to nuclear households, labor allocation expressed in number of person-days per hectare is higher among extended households for all activities. However, there is no significant statistical difference in sorghum yield across the two types of household structure. Finally, Tables 2.4 and 2.5 present descriptive statistics for household demographic and production characteristics after restricting the sample to households in the lower three quintiles of land holdings. As we highlight above, the motivation for such a restriction is to ensure that total land holding is not the main source of differences in the ITT estimates across extended and nuclear households.

Overall, much of the mean differences previously observed in Table 2.2 subsides or no longer exists. For example, not only is total land holding balanced by household structure, but so too are total sorghum land, fertilizer application rates, and total sorghum production.

Table 2.4 Demographic Characteristics Across Extended and Nuclear Households (Restricted Sample)

	Nuclear HHs (N=496)		**Extended HHs (N=181)**		
VARIABLES	Mean	SD	Mean	SD	P-Value
Household is Assigned Treatment	0.66	0.48	0.65	0.48	0.997
Head Age	45.09	14.32	52.01	15.93	0.000
Number of Adult Males	1.776	1.096	3.243	1.357	0.000
Number of Adult Females	1.976	1.121	3.624	1.681	0.000
Household size (members older than 15 years)	4.141	1.712	7.215	2.360	0.000

Note: Observations are at the household level. Sample is restricted to the lower three quintiles of land holding

Table 2.5 Production Characteristics Across Extended and Nuclear Households (Restricted Sample)

	Nuclear HHs (N=496)		**Extended HHs (N=181)**		
VARIABLES	Mean	SD	Mean	SD	P-Value
Household Uses Fertilizer	**0.379**	**0.486**	**0.464**	**0.500**	**0.080**
Intensity of fertilizer (kg/ha)	9.898	22.40	11.81	18.63	0.245
Total Land Holding (ha)	**1.839**	**0.779**	**1.940**	**0.775**	**0.094**
Total land where sorghum is main crop (ha)	**1.882**	**0.905**	**2.109**	**1.601**	**0.049**
Total land where millet is main crop (ha)	0.749	1.277	1.006	1.410	0.033
Total land where maize is main crop (ha)	0.0462	0.211	0.0762	0.279	0.162
Total land where rice is main crop (ha)	0.00479	0.0436	0.122	1.489	0.313
Total land where peanut is main crop (ha)	0.0286	0.165	0.0138	0.0902	0.161
Labor Allocation to Plowing (person-days/ha)	10.16	10.83	14.15	14.57	0.003
Labor Allocation to Planting (person-days/ha)	14.52	11.60	18.74	12.76	0.000
Labor Allocation to Fertilizer Application (person-days/ha)	2.636	4.855	3.968	6.046	0.008
Labor Allocation to Manure Application (person-days/ha)	4.899	6.367	7.064	8.882	0.004
Labor Allocation to Weeding (person-days/ha)	41.28	42.21	48.32	37.83	0.027
Labor Allocation to Harvest (person-days/ha)	16.19	15.66	21.95	17.32	0.001
Total Labor Allocation (person-days/ha)	89.75	66.29	114.2	67.08	0.000
Total sorghum production	**1,188**	**966.0**	**1,352**	**1,053**	**0.099**
Total sorghum yield (kg/ha)	705.0	605.4	689.7	574.5	0.751

Note: Observations are at the household level. Sample is restricted to the lower three quintiles of land holding

2.4.3 Pre-Treatment Household Demographic and Production Characteristics

In order to attribute any changes in labor allocation among assigned households to the microdosing treatment, it is important to ensure that households assigned to treatment and control groups share similar pre-intervention characteristics. Since we are interested in the heterogeneous effects of the microdosing treatment by household structure, we conduct balancing tests across treated and control households within each category of household structure.

Table 2.6 presents summary statistics of pre-intervention household demographic and production characteristics by assignment status for extended and nuclear households (see Panels A and B). All p-values corresponding to the statistical significance level of the mean differences across the assigned and control households greatly exceed the 10 percent significance level, indicating that the randomization produced balanced assignment and control groups of households.

Finally, Table 2.7 presents balancing tests by treatment assignment within household structure after restricting the sample to households in the lower three quintiles of total land holdings. Overall, the balance observed in Table 4 is preserved in the restricted sample. As a result, any differences in the ITT observed across nuclear and extended family households can be attributed to the heterogeneous impact of the treatment assignment by household structure.

Table 2.6 Balancing Test Results Across Assigned and Control Households by Household (Full sample)

	Panel A: Extended Households					**Panel B: Nuclear Households**				
	Control (N=120)		Assigned (N=234)			Control (N=240)		Assigned (N=465)		
VARIABLES	Mean	SD	Mean	SD	P-Value	Mean	SD	Mean	SD	P-Value
Head Age	52.08	15.66	52.1	15.3	0.994	46.27	14.38	45.95	14.02	0.785
Number of Adult Males	3.525	1.773	3.632	1.678	0.674	1.858	1.009	1.927	1.187	0.498
Number of Adult Females	4.092	1.879	4.184	2.39	0.742	2.192	1.296	2.178	1.218	0.9
Total number of adults	8.008	2.932	8.124	3.63	0.795	4.529	1.785	4.443	1.868	0.615
Household more than one married male	0.85	0.359	0.893	0.31	0.318	0	0	0	0	.
Household head has at least one married son	0.483	0.502	0.483	0.501	0.994	0	0	0	0	.
Household head has at least one married brother	0.25	0.435	0.252	0.435	0.964	0	0	0	0	.
Household head has at least one daughter-in-law	0.483	0.502	0.444	0.498	0.518	0	0	0	0	.
Household head has at least one sister-in-law	0.358	0.482	0.385	0.488	0.67	0	0	0	0	.
Household Uses Fertilizer	0.392	0.49	0.521	0.501	0.107	0.338	0.474	0.417	0.494	0.157
Intensity of fertilizer (kg/ha)	8.124	16.75	10.74	15.51	0.218	7.368	19.41	9.768	20.87	0.286
Total Land Holding (ha)	4.324	3.029	3.974	3.046	0.46	2.977	2.066	2.782	1.952	0.401
Total land where sorghum is main crop (ha)	4.672	3.652	4.234	3.523	0.449	3.009	2.11	2.869	2.154	0.551
Labor Allocation to Plowing (person-days/ha)	11.62	14.32	11.2	10.5	0.817	9.319	9.517	10.02	10.13	0.486
Labor Allocation to Planting (person-days/ha)	15.25	10.5	15.84	10.9	0.688	13.54	9.754	13.66	10.94	0.896
Labor Allocation to Fertilizer Application (person-days/ha)	2.957	5.046	3.413	5.236	0.472	2.077	4.167	2.551	4.587	0.357
Labor Allocation to Manure Application (person-days/ha)	4.761	6.29	6.203	7.6	0.108	5.074	6.917	4.432	5.401	0.34
Labor Allocation to Weeding (person-days/ha)	38.1	28.42	41.21	33.22	0.385	38.6	35.14	36.85	38.92	0.562
Labor Allocation to Harvest (person-days/ha)	16.35	13.36	18.41	14.52	0.261	14.65	11.62	14.95	14.93	0.786
Labor Allocation (person-days/ha)	89.11	57.31	96.33	57.91	0.34	83.37	59.13	82.5	60.81	0.859
Total sorghum yield (kg/ha)	537.4	544.3	607.6	438.4	0.259	671	640.1	609.3	490.1	0.225

Note: Observations are at the household level

Table 2.7 Balancing Test Results Across Assigned and Control Households by Household (Restricted sample)

	Panel A: Extended Households					**Panel B: Nuclear Households**				
	Control (N=58)		Assigned (N=123)			Control (N=159)		Assigned(N=337)		
VARIABLES	Mean	SD	Mean	SD	P-value	Mean	SD	Mean	SD	P-value
Head Age	53.17	16.92	51.45	15.47	0.55	45.24	14.34	45.03	14.33	0.88
Number of Adult Males	3.10	1.25	3.31	1.40	0.38	1.78	1.00	1.77	1.14	0.96
Number of Adult Females	3.72	1.67	3.58	1.69	0.57	1.96	1.05	1.98	1.16	0.84
Total number of adults	7.28	2.24	7.19	2.42	0.80	4.20	1.60	4.12	1.76	0.70
HH more than one married male	0.85	0.37	0.88	0.33	0.50	-	-	-	-	.
HH head has at least one married son	0.26	0.44	0.23	0.42	0.61	-	-	-	-	.
HH head has at least one married brother	0.52	0.50	0.44	0.50	0.30	-	-	-	-	.
HH head has at least one daughter-in-law	0.52	0.50	0.35	0.48	0.03	-	-	-	-	.
HH head has at least one sister-in-law	0.31	0.47	0.37	0.49	0.37	-	-	-	-	.
HH Uses Fertilizer	0.36	0.49	0.51	0.50	0.30	0.33	0.47	0.40	0.49	0.56
Intensity of fertilizer (kg/ha)	8.99	19.57	13.14	18.10	0.77	9.10	22.72	10.27	22.27	0.19
Total Land Holding (ha)	2.01	0.83	1.91	0.75	0.54	1.85	0.76	1.84	0.79	0.68
Total land where sorghum is main crop (ha)	2.07	0.83	2.13	1.86	0.12	1.86	0.76	1.89	0.97	0.26
Labor Allocation to Plowing (person-days/ha)	13.91	18.90	14.27	12.10	0.91	10.12	10.73	10.17	10.90	0.97
Labor Allocation to Planting (person-days/ha)	18.35	12.85	18.92	12.76	0.81	14.94	11.01	14.33	11.88	0.60
Labor Allocation to Fertilizer Application (person-days/ha)	3.02	5.53	4.42	6.25	0.14	2.34	4.42	2.77	5.05	0.46
Labor Allocation to Manure Application (person-days/ha)	5.42	7.64	7.84	9.34	0.10	5.53	7.57	4.60	5.70	0.26
Labor Allocation to Weeding (person-days/ha)	46.84	34.99	49.02	39.22	0.71	44.94	39.66	39.56	43.31	0.16
Labor Allocation to Harvest (person-days/ha)	19.78	17.64	22.97	17.14	0.34	16.53	13.26	16.02	16.69	0.74
Labor Allocation (person-days/ha)	107.30	71.71	117.50	64.83	0.42	94.56	65.96	87.48	66.42	0.27
Total sorghum yield (kg/ha)	663.60	711.00	702.00	500.40	0.70	775.10	732.0	671.90	533.50	0.13

Note: Observations are at the household level. Sample is restricted to the lower three quintiles of land holding

2.5 Results

2.5.1 Results with the full sample

The primary focus of this paper is the heterogeneity of the treatment effect by household structure. However, since the treatment provided enough fertilizer and seed for a small parcel (one half hectare), one might expect that smaller landholders may be more greatly affected by the intervention in comparison to larger landholders. Thus, baseline land holdings may be a potentially important factor in determining the effectiveness of the treatment on labor allocation. Consequently, we present two sets of results in Panels A and B in Table 2.8 corresponding to equations (2.2) and (2.3).

Three models are presented in each panel. Model A1 in Panel A includes the treatment assignment and the log of baseline land holdings as well as their interaction terms. Model A2 adds commune fixed effects to account for the potential effects of location-specific unobservables. These include factors such as access to inputs, labor and output markets, as well as differences in social and cultural norms that are likely to affect self-selection into a particular household structure. In Model A3, we add a binary indicator of household structure (extended households, with nuclear households being the comparison). We also add the share of total land devoted to sorghum cultivation in Model A3 because the prevalence of sorghum production in the household could affect labor allocation to sorghum production activities such as microdosing, with potential labor constraints to adoption decisions. The specifications in Panel B are analogous to those in Panel A, where the interaction term is now between household structure and treatment status.

Table 2.8 Changes in log of labor allocation across baseline and follow-up (Full Sample)

Panel A: Interaction with log of land			
VARIABLES	Model A1	Model A2	Model A3
Assigned	-0.013	0.013	0.014
	(0.14)	(0.15)	(0.15)
Logland	0.383***	0.432***	0.442***
	(0.08)	(0.08)	(0.08)
Assigned*Logland	0.036	-0.004	-0.004

Table 2.8 (cont'd)

	(0.10)	(0.10)	(0.10)
Extended			0.006
			(0.06)
Sorghum land share			-0.077
			(0.16)
Commune FE included	No	Yes	Yes
Observations	1,059	1,059	1,059
R-squared	0.060	0.117	0.117
Panel B: Interaction with household structure			
VARIABLES	Model B1	Model B2	Model B3
Assigned	0.081	0.074	0.079
	(0.079)	(0.073)	(0.072)
Extended	0.264***	0.263***	0.142
	(0.095)	(0.094)	(0.100)
Assigned*Extended	-0.205*	-0.223**	-0.206*
	(0.114)	(0.110)	(0.111)
Logland			0.437***
			(0.056)
Sorghum land share			-0.073
			(0.14)
(β1+β3)	-0.125	-0.150	-0.126
P-value of F-test (β1+β3)=0	0.166	0.088	0.144
Commune FE included	No	Yes	Yes
Observations	1,059	1,059	1,059
R-squared	0.008	0.120	0.120

Note: Household level regressions. Standard errors clustered by village in parentheses. * p<0.1 ** p<0.05 *** p<0.01. Only households with at least one male-controlled plot where sorghum is main crop across baseline and follow-up are included in all regressions. For extended household definition, see section 3. Logland and sorghum land share are baseline observations

For the specification with respect to household structure in Panel B, Table 2.8, the ITT effect of the intervention for nuclear households is captured by the coefficient on the variable "Assigned" (i.e., β1). Here, even though the program seems to not have induced significant changes in labor allocation among nuclear households in treatment villages, the magnitude of the coefficients is much larger relative to those in Panel A in Table 2.8 with relatively smaller standard errors. This indicates that the program may have induced a slight increase in labor allocation among nuclear households. As the overall effect on extended households is the sum of the coefficient estimates on the treatment variable and the interaction term (i.e., $\beta 1+\beta 3$), the net effect for these households is -0.125, -0.150, and -0.126, across Model B1, B2, and B3, respectively. These negative coefficients imply that the microdosing intervention induced a decrease in labor allocation among extended households. The magnitude of each of these sums is relatively high, providing suggestive evidence of heterogeneous impact of the treatment assignment by household structure (though the sums of these coefficients are only marginally statistically different from zero; see Table 2.8, Panel B).

2.5.2 Results with the restricted sample

As shown in Table 2.2, there is a large disparity between pre-program landholdings across nuclear and extended family households. Sorghum land holdings among extended family households is almost 50 percent larger. It is therefore possible that the results presented thus far could be a mere artifact of differences in baseline land holdings across nuclear and extended households. To rule out this possibility, we carry out additional regressions with the sample restricted to the lower three quintiles of land holdings, where we have relatively balanced land holdings by household structure as well as other important production characteristics such as fertilizer use rates, total land devoted to sorghum cultivation, and total sorghum production (see Table 3.2). One important point in the results with the restricted sample in Table 2.4 is that while production characteristics tend to be relatively balanced across extended and nuclear households, household demographics remain significantly different. Therefore, differences in treatment impact across extended and nuclear households in the restricted sample can be attributed to the heterogeneous impact of the program by household structure.

The results obtained with the restricted sample are presented in Table 7. Similar to the results with the full sample, there is no evidence of heterogeneous treatment impact by baseline landholding in the specification where treatment assignment is interacted with log of landholdings (see Models A1, A2, and A3 in Panel A, Table 2.9).

When we interact treatment assignment and household structure, we find a significant difference in ITT estimates by household structure regardless of the model specification (Panel B, Table 2.9). Particularly, in Model B3, where we include both baseline landholdings and sorghum land share, as well as commune fixed effects, we find that assignment to treatment induced nuclear households to increase labor allocation to sorghum production by approximately 17 percent and this is statistically different from zero at the 5 percent significance level. With the baseline mean value of total labor allocation being about 90 person-days per hectare, this corresponds to an increase of nearly 15 person-days per hectare among nuclear households. This finding is consistent with the fact that the microdosing technique is labor intensive.

Table 2.9 Changes in log of labor allocation across baseline and follow-up (Restricted Sample)

Panel A: Interaction with log of land

VARIABLES	Model A1	Model A2	Model A3
Assigned	-0.196	-0.223	-0.215
	(0.24)	(0.25)	(0.25)
Logland	0.217	0.21	0.247
	(0.20)	(0.20)	(0.20)
Assigned*Logland	0.24	0.255	0.25
	(0.24)	(0.24)	(0.24)
Extended			-0.198
			(0.16)
Sorghum land share			0.026
			(0.07)
Commune FE included	No	Yes	Yes
Observations	677	677	677
R-squared	0.019	0.097	0.100

Panel B: Interaction with household structure

VARIABLES	Model B1	Model B2	Model B3
Assigned	0.159*	0.165**	0.163**
	(0.090)	(0.079)	(0.081)
Extended	0.373***	0.368***	0.328***
	(0.116)	(0.112)	(0.112)

Table 2.9 (cont'd)

Assigned*Extended	-0.431***	-0.464***	-0.451***
	(0.145)	(0.142)	(0.139)
Logland			0.411***
			(0.114)
Sorghum land share			-0.196
			(0.16)
(β1+β3)	-0.272	-0.299	-0.288
P-value of F-test (β1+β3) = 0	0.032	0.014	0.013
Commune FE included	No	Yes	Yes
Observations	677	677	677
R-squared	0.060	0.117	0.117

Note: Note: Household level regressions. Standard errors clustered by village in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$. Sample restricted to the first three quintiles of total sorghum land holding. Only households with at least one male-controlled plot where sorghum is main crop across baseline and follow-up are included in all regressions. For extended household definition, see section 3. Logland and sorghum land share are baseline observations

While the program induced an increase in labor allocation among nuclear households, the results suggest that it had the opposite effect on extended households. The differential impact by household structure is shown by the negative coefficient on the interaction term. Assigned*Extended (i.e., β3), which is -0.45 and is statistically significant at the 1 percent level (Model B3, Panel B, Table 2.9). This implies that overall, the impact of the program on total labor allocated to sorghum production among extended households is approximately 45 percent lower relative to its impact on nuclear households.

The net impact on the extended households, which is the sum of the coefficients (β1+β3), is negative 0.29. The descriptive statistics presented in Table 2.5 show that baseline total labor allocated to sorghum production among the extended households in the restricted sample is about 114 person-days per hectare. Consequently, the negative 0.29 indicates that the microdosing intervention induced a reduction in labor allocation for sorghum production by about 33 person-days per hectare among the extended households. These results provide evidence that the prior estimates in Table 2.8 may have underestimated differences in ITT effects of the intervention by household structure.

To understand how the intervention increased total labor allocation among the assigned nuclear households, we present results for specific activities in Table 2.10. Here, we focus on Model B3, where treatment is interacted with household structure using the most exhaustive specification –that is, where we control for baseline land holdings, sorghum land share and commune fixed effects. The outcome variables are changes (across pre- and post-intervention periods) in time spent on: plowing, planting, manure application, inorganic fertilizer application, weeding, and harvest, and are all expressed in log.

Labor allocation results with respect to fertilizer application indicate that the program had a significant impact for all treated households, by up to 42 percent and 57 percent , respectively, for nuclear and extended households. Based on the baseline average values presented in Table 2.5, these results indicate that the treatment induced an increase of about 1 and 2 person-days per hectare on time devoted to inorganic fertilizer application, respectively, among nuclear and extended households. This increase in fertilizer labor suggests that the beneficiary households did use the fertilizer in their field.

Table 2.10 Labor allocation results by activity using sample restricted to the lower three quintiles of total sorghum land

VARIABLES	Plowing	Planting	Manure	Fertilizer	Weeding	Harvest
Assigned (β1)	-0.003	0.169**	0.138	0.421***	0.141	0.214**
	(0.13)	(0.08)	(0.11)	(0.12)	(0.12)	(0.10)
Extended	-0.143	0.266**	0.518**	-0.123	0.427*	0.352***
	(0.22)	(0.13)	(0.20)	(0.21)	(0.22)	(0.13)
Assigned*Extended (β3)	0.002	-0.324**	-0.568**	0.153	-0.480*	-0.397**
	(0.26)	(0.16)	(0.24)	(0.28)	(0.28)	(0.18)
Logland	-0.316	-0.22	-0.421*	0.092	0.192	-0.18
	(0.22)	(0.17)	(0.22)	(0.23)	(0.24)	(0.19)
Sorghum land share	0.348	0.405***	0.139	-0.045	0.057	0.491***
	(0.22)	(0.13)	(0.19)	(0.19)	(0.22)	(0.16)
(β1+β3)	-0.00	-0.155	-0.430*	0.574**	-0.339	-0.182
P-value of (β1+β3) = 0	0.997	0.267	0.061	0.028	0.161	0.239
Commune FE included	Yes	Yes	Yes	Yes	Yes	Yes
Observations	677	677	677	677	677	677
R-squared	0.101	0.055	0.090	0.063	0.142	0.081

Note: Household level regressions. Standard errors clustered by village in parentheses. * p<0.1 ** p<0.05 *** p<0.01. Sample restricted to the first three quintiles of total sorghum land holding. Only households with at least one male-controlled plot where sorghum is main crop across baseline and follow-up are included in all regressions. For extended household definition, see section 3. Logland and sorghum land share are baseline observations

While the program seems to have similarly affected nuclear and extended households in terms of their labor devoted to inorganic fertilizer application, ITT estimates with respect to the other labor activities indicate that the program positively affected nuclear households only, and in some instances had the opposite effect on extended households. This is shown by the positive and significant coefficient $\beta1$ for labor allocated to planting and harvest, and the negative interaction term between Assigned and Extended, which is also statistically significant (i.e. $\beta3$). Given that the overall effect on extended household is ($\beta1+\beta3$), the net effect on these households is negative, although not statistically different from zero. With respect to time spent on manure application, the program induced a significant decrease among extended households, while no significant changes are detected among nuclear households.

The estimation by labor (i.e., male, female, or child labor), presented in Table 2.11, reveals that the heterogeneous impact of the treatment mostly comes from male labor allocation followed by female labor. As for child labor, there are no discernible differences across the two types of household structure.

Table 2.11 Changes in log of labor allocation across baseline and follow-up by labor source (Restricted sample)

	Male labor			Female labor			Child labor		
VARIABLES	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Assigned (β1)	0.144	0.190**	0.189**	0.222**	0.186*	0.182*	-0.031	0.07	0.072
	(0.097)	(0.084)	(0.087)	(0.103)	(0.107)	(0.109)	(0.213)	(0.174)	(0.179)
Extended	0.470***	0.468***	0.424**	0.367**	0.336**	0.314**	0.321	0.405	0.378
	(0.158)	(0.170)	(0.168)	(0.146)	(0.147)	(0.155)	(0.356)	(0.321)	(0.328)
Assigned*Extended (β3)	-0.503**	-0.547***	-0.533***	-0.384**	-0.369**	-0.359*	-0.239	-0.371	-0.365
	(0.192)	(0.202)	(0.196)	(0.190)	(0.184)	(0.189)	(0.414)	(0.390)	(0.392)
Logland			-0.294*			0.008			-0.362
			(0.174)			(0.189)			(0.363)
Sorghum land share			0.377***			0.385**			0.009
			(0.142)			(0.164)			(0.326)
(β1+β3)	-0.360	-0.356	-0.344	-0.162	-0.183	-0.177	-0.270	-0.301	-0.293
P-value of (β1+β3) =0	0.018	0.034	0.031	0.385	0.284	0.304	0.490	0.345	0.357
Commune FE included	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	677	677	677	677	677	677	677	677	677
R-squared	0.014	0.077	0.090	0.010	0.063	0.074	0.002	0.071	0.073

Note: Note: Household level regressions. Standard errors clustered by village in parentheses. * p<0.1 ** p<0.05 *** p<0.01. Sample restricted to the first three quintiles of total sorghum land holding. Only households with at least one male-controlled plot where sorghum is main crop across baseline and follow-up are included in all regressions. For extended household definition, see section 3. Logland and sorghum land share are baseline observations.

2.6 Understanding the sources of the heterogeneous impact of the program

The heterogeneous impact by household structure may be attributed to several reasons. One important feature of the microdosing application technique is that it is labor intensive, especially at planting and fertilizer application times. Thus, the lack of increase in the overall labor allocated to sorghum production among the extended households, despite suggestive evidence that these households applied the fertilizer distributed to them on their sorghum field, is puzzling. This is especially startling, given that these households are more likely to have a larger pool of labor relative to the nuclear households given their larger size. While the differential impact of the intervention by household structure is counter-intuitive, we offer a few factors that may rationalize the current findings.

2.6.1 Labor fixity within the extended households and differences in incentive?

One plausible factor associated with the heterogeneous effect of the intervention is that extended household members may face fixed labor or some coordination costs in the reallocation of their labor. As a result, the increased labor requirement in fertilizer application may have substituted labor away from other activities. This speculation is supported by the significant reduction in the time spent on manure application among extended households.

To investigate whether the microdosing substituted labor away from the production of the other crops, especially for the nuclear households who experienced an increase in labor allocated to sorghum production, we estimate changes in labor allocation with respect to the other crops. Two noteworthy findings must be highlighted in the corresponding results presented in Table 2B (APPENDIX B). First, we find that the treatment did not induce any changes in the amount of labor allocated to the production of the other crops. Second, there is no indication of heterogeneous impact of the program by household structure. One of the immediate implication of these results is that the intervention did not substitute labor away from the production of the other crops. This corroborates our assumption that the increase in the time spent on fertilizer application for sorghum production among the extended households resulted from a decrease in manure application time for the same crop, indicating labor fixity among these households.

A pressing question is: *Where did the increased time spent on sorghum production among the nuclear households come from?* One may stipulate that the program led nuclear households to adjust the share of total land devoted to sorghum cultivation to adequately respond to the labor requirement of the microdosing technology. However, this claim is not sustained by the data, as results presented in Table 2C (APPENDIX C) do not show any evidence of changes in the share of sorghum land, neither by treatment status, nor by household structure. The results with respect to changes in the number of plots presented in the same table yielded no noticeable differences either. Based on these results, our assumption is that the microdosing intervention induced nuclear households to exert more effort by spending more time on their sorghum production.

How might have the microdosing induced labor increase among the nuclear households? Recall that one important distinction between nuclear and extended households in terms of their production organization is the coexistence of collective and individual plots within the extended households (West, 2010; Kazianga and Wahhaj, 2013; Guirkinger and Platteau, 2014). Labor allocation across the two types of plots requires managers of the individual plots, who are junior members relative to the head, to provide labor on the collective plots, which are managed by the head, before working on their individual plots. Production from the collective plots is shared among all extended family members. The sharing rule is mostly based on need instead of effort provision (Guirkinger and Platteau, 2014) either by taking common meals or distributing output to each nuclear household (Beaman and Dillon, 2012).[53]

With this sharing scheme within the extended households, an increase in effort provided by an individual does not necessarily translate into an increase in her / his reward. In contrast, within the pure nuclear households, production is for the head, his spouse(s), unmarried children, and other immediate dependents. Consequently, for the nuclear households, any accrued production from the microdosing

[53] One may argue that the higher labor allocation among the nuclear households relative to the extended households is due to moral hazard on the collective plots within the extended households. While the available data do not allow us to rule out this possibility, we claim that the issue of moral hazard is unlikely to be a driving factor based on compelling evidence in the empirical literature that, because of social norms, collective plots receive much more labor relative to individual plots among households in the same region (Kazianga and Wahhaj, 2013).

technology is the sole ownership of these households, which may provide them with greater incentives to exert more effort to their sorghum production activities following the reception of the kits.

Furthermore, labor endowment is more likely to be centralized at the head's level within the pure nuclear households, enabling the later to make household members spend longer times on sorghum plots that received the microdosing kit to respond to the increased labor requirement. Conversely, in the extended households where multiple nuclear households exist, labor division is such that members can only work for a certain amount of time on the collective plots, after which they switch to their own individual plots. The potential constraint that this labor division imposes on the time spent on the collective plots may also constitute a plausible reason for the heterogeneous impact of the intervention by household structure.

2.6.2 Differences in productive resource control within the extended households?

The claims of fixed labor and differences in incentives by household structure provided above stem from the assumption that the microdosing kit is applied on the collective plots within the extended households. However, any sorghum grower in the household was eligible to be randomly selected to receive the kit. Given that junior plot managers are required to work on the collective plots before working on their individual plots , another plausible source of the differential impact of the microdosing program by household structure could be the following: if the recipient of the microdosing kit in the extended household is a junior plot manager with less control over productive resources within the household compared to the household head, he may not be able to mobilize the required labor for the technology on his plot.

Plot-manager level regression results are presented in Table 2D (APPENDIX D). Overall, we do not find any significant differences in changes in total labor allocated to sorghum production by headship.[54] However, the analysis by specific activity reveals that recipients of the microdosing kits who

[54] Note from the description of our intervention that there is only one recipient by household.

are heads of households experienced a significant increase in time spent on fertilizer application relative to non-head members.

We also run regressions where we control the headship of the recipient across nuclear and extended households (results not reported here). We did not detect any significant statistical difference due to imprecise estimates, certainly because of low variation in the headship of the recipient, especially among nuclear households. Indeed, up to 96 percent of the recipients in the nuclear households are heads of households, while the corresponding figure for extended households is about 81 percent.

Because almost all recipients in the nuclear households are heads, we ran additional regressions where we keep a sample of extended households only to investigate differences across head and non-head recipients. Overall. The results (see APPENDIX E) remain robust, confirming that recipients who are heads experienced a larger increase in their labor allocation compared to non-head recipients.

2.7 Conclusion and policy implications

We have shown that there are significant heterogeneous impacts of the microdosing program by household structure. Specifically, we find that the intervention increased labor allocation to sorghum production among nuclear households, which is consistent with the fact that the microdosing technique is labor intensive. We find no indication that the increase in labor allocated to sorghum production among these households resulted from labor being substituted away from the production of the other crops.

In contrast, for the extended households, we find that the increased labor requirement for fertilizer application substituted labor from time spent on manure application, resulting into an overall decrease in the total amount of labor allocation to sorghum production. These findings are startling, given the presumably bigger pool of labor available to the extended households due to their larger size. We explain this unanticipated heterogeneous impact of the intervention by a couple of factors stemming from differences in the production system across the two types of households.

First, we attribute the increase in labor allocation among the nuclear households to higher incentives for the latter to exert more effort in their sorghum production following the reception of the kits. Nuclear households are sole claimants of their production and, consequently, can keep any potential increase in sorghum production following the introduction of the microdosing technology. In contrast, in the extended households, where multiple nuclear families coexist, members jointly work on collective plots and share production among themselves based on the need of each nuclear family, instead of the level of their efforts. Consequently, if the microdosing is applied on a collective plot within the extended households, the incitation to meet the increased required labor will be lower among these households relative to the nuclear households.

Furthermore, extended family members can only allocate a certain amount of time on the collective plots as they must also allocate part of their labor on their own individual plots. This cap on the amount of time that can be spent on the collective plots limits the ability of these households to meet the labor increase induced by the adoption of the microdosing. This is backed by the suggestive evidence that extended households reduced the amount of time spent on manure application to meet the additional labor required for fertilizer application.

Labor constraint on sorghum plots receiving the microdosing technology also holds when the technology is applied on individual plots, especially, if the recipient is a non-head member, who has relatively less control over productive resources relative to the head of household. We support this claim with suggestive evidence indicating that recipients of the microdosing kits who are heads of households experienced a greater increase in labor allocated to fertilizer application relative to those who are non-head members.

Despite some limitations in the interpretation of our results, the current findings have important implications for agricultural development policy interventions in developing countries, where increasing fragmentation of households to smaller units has led to heterogeneity in household structures. Most agricultural technologies in the developing world, especially among small scale subsistence farmers, tend to be labor intensive. At the same time, these households face missing labor markets and must resort to their own members to satisfy their labor need such that household composition becomes an important determinant of labor endowment. As a result, the differential impact of the microdosing intervention by household structure highlights the importance of understanding households labor allocation decision making depending on their structure for successful implementation of agricultural development interventions. This is important for the promotion of labor-intensive technologies among farmers who face labor constraints due to limited control over productive resources and missing labor markets.

Another implication for the increased labor among the nuclear households is that they would be more likely to adopt labor intensive agricultural technologies. This, combined with the importance of technology adoption for increased agricultural productivity and the increasing fragmentation of larger households into smaller units, the current findings suggest high potential for future agricultural intensification. These implications reconcile with findings among similar population in Burkina Faso, where the authors find more productive efficiency among nuclear households relative to extended households.

APPENDICES

APPENDIX A MICRODOSING TAKE-UP BY HOUSEHOLD STRUCTURE

Table 2A. Take-up of microdosing by household structure after program implementation

	Nuclear treated HHs		Extended treated HHs		
	Mean	SD	Mean	SD	P-value of diff
Full sample	0.652	0.477	0.676	0.469	0.435
Restricted sample	0.668	0.471	0.629	0.484	0.333

APPENDIX B CHANGES IN LABOR ALLOCATION FOR NON SORGHUM CROPS

Table 2B. Changes in labor allocation across baseline and follow-up for crops other than sorghum

VARIABLES	Total	Plowing	Planting	Fertilizer	Manure	Weeding	Harvest
Assigned	0.01	0.035	-0.047	0.049	0.089	-0.037	0.057
	(0.09)	(0.16)	(0.11)	(0.14)	(0.16)	(0.14)	(0.12)
Extended	0.093	0.28	-0.009	0.144	0.139	0.208	0.117
	(0.13)	(0.24)	(0.13)	(0.20)	(0.27)	(0.20)	(0.21)
Assigned*Extended	-0.23	-0.467	-0.13	-0.058	-0.139	-0.404	0.022
	(0.17)	(0.30)	(0.17)	(0.28)	(0.29)	(0.28)	(0.26)
Sorghum land share	-0.2	0.244	-0.385	0.341	-0.171	0.099	-0.619*
	(0.28)	(0.41)	(0.29)	(0.41)	(0.54)	(0.40)	(0.36)
Logland	0.318**	0.202	0.353**	0.165	0.095	0.169	0.259*
	(0.15)	(0.19)	(0.14)	(0.19)	(0.25)	(0.20)	(0.15)
Commune FE included	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	482	482	482	482	482	482	482
R-squared	0.089	0.098	0.105	0.077	0.071	0.191	0.104

Note: Household level regressions. Standard errors clustered by village in parentheses. * $p<0.1$ ** $p<0.05$ *** $p<0.01$. Only households with at least one male-controlled plot where sorghum is main crop across baseline and follow-up are included in all regressions. For extended household definition, see section 3. Logland and sorghum land share are baseline observations. Smaller number of observations as only few households have male-controlled plots where sorghum is not the main crop

APPENDIX C CHANGES IN SORGHUM LAND SHARE AND NUMBER OF PLOTS

Table 2C. Changes in sorghum land share and number of plots across baseline and follow-up

	Changes in sorghum land share			Changes in number of plots		
VARIABLES	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Assigned	0.021	-0.004	-0.006	0.168	0.075	0.065
	(0.025)	(0.023)	(0.022)	(0.103)	(0.089)	(0.082)
Extended	0.001	-0.003	0.031	-0.187	-0.175	0.066
	(0.025)	(0.025)	(0.025)	(0.151)	(0.156)	(0.125)
Assigned*Extended	-0.028	-0.026	-0.031	-0.055	-0.063	-0.098
	(0.033)	(0.034)	(0.034)	(0.174)	(0.180)	(0.152)
Logland			-0.129***			-0.889***
			(0.017)			(0.070)
Commune FE included	No	No	Yes	No	No	Yes
Observations	1,059	1,059	1,059	1,059	1,059	1,059
R-squared	0.002	0.045	0.096	0.0136	0.0629	0.2095

Note: Household level regressions. Standard errors clustered by village in parentheses. * p<0.1 ** p<0.05 *** p<0.01. Only households with at least one male-controlled plot where sorghum is main crop across baseline and follow-up are included in all regressions. For extended household definition, see section 3. Logland and sorghum land share are baseline observations.

APPENDIX D CHANGES IN LABOR ALLOCATION BY HEADSHIP AT THE PLOT-MANAGER LEVEL

Table 2D. Changes labor allocation across heads and non-heads members between baseline and follow-up (All male plot managers)

VARIABLES	Total labor	Plowing	Planting	Fertilizer	Manure	Weeding	Harvest
Recipient is head	0.072	0.06	0.061	0.275***	0.093	0.041	0.054
	(0.05)	(0.08)	(0.05)	(0.07)	(0.09)	(0.08)	(0.06)
Sorghum land share	-0.254**	-0.248	-0.149	0.119	-0.453**	-0.211	-0.351**
	(0.12)	(0.19)	(0.13)	(0.16)	(0.18)	(0.16)	(0.15)
Logland	0.230***	0.213***	0.260***	0.085	0.114*	0.133*	0.257***
	(0.04)	(0.07)	(0.05)	(0.06)	(0.07)	(0.07)	(0.05)
Commune FE included	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,150	1,150	1,150	1,150	1,150	1,150	1,150
R-squared	0.0633	0.0482	0.056	0.054	0.0553	0.0884	0.0617

Note: Plot-manager level regressions. Standard errors clustered at the household level in parentheses. * p<0.1 ** p<0.05 *** p<0.01. Only male plots managers with at least one plot where sorghum is main crop across baseline and follow-up are included in all regressions. Logland and sorghum land share are baseline observations.

APPENDIX E CHANGES IN LABOR ALLOCATION BY HEADSHIP AT PLOT-MANAGER LEVEL (EXTENDED HOUSEHOLDS ONLY)

Table 2E. Changes labor allocation across heads and non-heads members between baseline and follow-up (All male plot managers within extended households)

VARIABLES	Total labor	Plowing	Planting	Fertilizer	Manure	Weeding	Harvest
Recipient is head	0.09	0.206	0.132	0.270**	0.054	0.071	0.015
	(0.091)	(0.138)	(0.096)	(0.134)	(0.159)	(0.137)	(0.109)
Sorghum land share	-0.347*	-0.14	-0.188	0.339	-0.836***	-0.446*	-0.298
	(0.201)	(0.323)	(0.247)	(0.245)	(0.315)	(0.233)	(0.250)
Logland	0.192***	0.300***	0.185**	-0.098	0.005	0.197*	0.142*
	(0.067)	(0.109)	(0.072)	(0.093)	(0.105)	(0.112)	(0.085)
Commune FE included	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	415	415	415	415	415	415	415
R-squared	0.107	0.119	0.078	0.111	0.130	0.109	0.068

Note: Plot-manager level regressions. Standard errors clustered at the household level in parentheses. * p<0.1 ** p<0.05 *** p<0.01. Only male plots managers with at least one plot where sorghum is main crop across baseline and follow-up are included in all regressions. Logland and sorghum land share are baseline observations.

REFERENCES

REFERENCES

Aune, J.B. and Coulibaly, A. (2015). Microdosing of Mineral Fertilizer and Conservation Agriculture for Sustainable Agricultural Intensification in Sub-Saharan Africa. In Sustainable Intensification to Advance Food Security and Enhance Climate Resilience in Africa (pp. 223-234). Springer International Publishing.

Barrett, C. B., Moser, C. M., McHugh, O. V., & Barison, J. (2004). Better technology, better plots, or better farmers? Identifying changes in productivity and risk among Malagasy rice farmers. American Journal of Agricultural Economics, 86(4), 869-888.

Beaman, L. and Dillon, A. (2012). Do household definitions matter in survey design? Results from a randomized survey experiment in Mali. Journal of Development Economics, 98(1), pp.124-135.

Becker, G. (1981). A Treatise on the Family. Cambridge, Mass.: Harvard University Press.

Bongaarts, J., 2001. Household size and composition in the developing world in the 1990s. Population studies, 55(3), pp.263-279.

Bielders, C.L. and Gérard, B. (2015). Millet response to microdose fertilization in southwestern Niger: effect of antecedent fertility management and environmental factors. Field Crops Research, 171, pp.165-175.

Colson, E. (1962). Family change in contemporary Africa. Annals of the New York Academy of Sciences, 96(2), pp.641-652.

Croppenstedt, A., Demeke, M., & Meschi, M. M. (2003). Technology adoption in the presence of constraints: the case of fertilizer demand in Ethiopia. Review of Development Economics, 7(1), 58-70.

De Janvry, A., Fafchamps, M., & Sadoulet, E. (1991). Peasant household behaviour with missing markets: some paradoxes explained. The Economic Journal, 101(409), 1400-1417.

Doss, C.R. (2001). Designing agricultural technology for African women farmers: Lessons from 25 years of experience. World development, 29(12), pp.2075-2092.

Doss, C. R. (2006). Analyzing technology adoption using microstudies: limitations, challenges, and opportunities for improvement. Agricultural Economics, 34(3), 207-219.

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

Evenson, R. E., & Gollin, D. (2003). Assessing the impact of the Green Revolution, 1960 to 2000. Science, 300(5620), 758-762.

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

Foster, A.D. and Rosenzweig, M.R. (2010). Microeconomics of technology adoption. Annu. Rev. Econ., 2(1), pp.395-424.

Galor, O. (2005). The demographic transition and the emergence of sustained economic growth. Journal of the European Economic Association, 3(2-3), pp.494-504.

Galor, O. and Weil, D.N. (2000). Population, technology, and growth: From Malthusian stagnation to the demographic transition and beyond. American economic review, pp.806-828.

Garnett, T., Appleby, M.C., Balmford, A., Bateman, I.J., Benton, T.G., Bloomer, P., Burlingame, B., Dawkins, M., Dolan, L., Fraser, D. and Herrero, M. (2013). Sustainable intensification in agriculture: premises and policies. Science, 341(6141), pp.33-34.

Giné, X., & Yang, D. (2009). Insurance, credit, and technology adoption: Field experimental evidence from Malawi. Journal of development Economics, 89(1), 1-11.

Guirkinger, C., & Platteau, J. P. (2014). The effect of land scarcity on farm structure: empirical evidence from Mali. Economic Development and Cultural Change, 62(2), 195-238.

Guirkinger, C., Platteau, J. P., & Goetghebuer, T. (2015). Productive inefficiency in extended agricultural households: Evidence from Mali. Journal of Development Economics, 116, 17-27.

ICRISAT. 2012. Fertilizer Microdosing, July 2012.

Jack, B. K. (2013). Market inefficiencies and the adoption of agricultural technologies in developing countries.

Jayne, T. S., Yamano, T., Weber, M. T., Tschirley, D., Benfica, R., Chapoto, A., & Zulu, B. (2003). Smallholder income and land distribution in Africa: implications for poverty reduction strategies. Food policy, 28(3), 253-275.

Just, R. E., & Zilberman, D. (1983). Stochastic structure, farm size and technology adoption in developing agriculture. Oxford Economic Papers, 35(2), 307-328.

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

Kazianga, H., & Wahhaj, Z. (2013). Gender, Social Norms, and Household Production in Burkina Faso. Economic Development and Cultural Change, 61(3), 539-576.

Kazianga, H., & Wahhaj, Z. (2017). Intra-household resource allocation and familial ties. Journal of Development Economics, 127, 109-132.

Kijima, Y., Otsuka, K. and Sserunkuuma, D., 2011. An inquiry into constraints on a green revolution in Sub-Saharan Africa: the case of NERICA rice in Uganda. World Development, 39(1), pp.77-86.

Khonje, M., Manda, J., Alene, A. D., & Kassie, M. (2015). Analysis of adoption and impacts of improved maize varieties in eastern Zambia. World Development, 66, 695-706.

Langyintuo, A. S., & Mungoma, C. (2008). The effect of household wealth on the adoption of improved maize varieties in Zambia. Food policy, 33(6), 550-559.

Laslett, P., Wall, R., Nakamura, J.I. and Miyamoto, M., 1982. Household and family in past time. Economic Development and Cultural Change, 30(2), pp.229-269.

Marenya, P. P., & Barrett, C. B. (2007). Household-level determinants of adoption of improved natural resources management practices among smallholder farmers in western Kenya. Food policy, 32(4), 515-536.

McMillan, D.E., 1987. Monitoring the evolution of household economic systems over time in farming systems research. Development and Change, 18(2), pp.295-314.

Mendola, M., 2008. Migration and technological change in rural households: Complements or substitutes? Journal of Development Economics, 85(1), pp.150-175.

Ministère de l'Agriculture, de l'Hydraulique et des Resources Halieutiques. 2010. Diagnostic du secteur Semencier du Burkina Faso. Document final. Ouagadougou, Burkina Faso, November.

Moreno, G., and Sunding, D. L. (2005). Joint estimation of technology adoption and land allocation with implications for the design of conservation policy. American Journal of Agricultural Economics, 87(4), 1009-1019.

Morton, J. F. (2007). The impact of climate change on smallholder and subsistence agriculture. Proceedings of the national academy of sciences, 104(50), 19680-19685.

Moser, C. M., & Barrett, C. B. (2003). The disappointing adoption dynamics of a yield-increasing, low external-input technology: the case of SRI in Madagascar. Agricultural Systems, 76(3), 1085-1100.

Noltze, M., Schwarze, S., & Qaim, M. (2012). Understanding the adoption of system technologies in smallholder agriculture: The system of rice intensification (SRI) in Timor Leste. Agricultural systems, 108, 64-73.

Poteete, A.R. and Ostrom, E. (2004). Heterogeneity, group size and collective action: The role of institutions in forest management. Development and change, 35(3), pp.435-461.

Resnick, D., Tarp, F., & Thurlow, J. (2012). The political economy of green growth: Illustrations from Southern Africa (No. 2012/11). WIDER Working Paper.Rosenzweig, M. R., & Wolpin, K. I. (1985). Specific experience, household structure, and intergenerational transfers: farm family land and labor arrangements in developing countries. The Quarterly Journal of Economics, 961-987.

Rosenzweig, M.R. and Wolpin, K.I. (1985). Specific experience, household structure, and intergenerational transfers: farm family land and labor arrangements in developing countries. Quarterly Journal of Economics, pp.961-987.

Teklewold, H., Kassie, M., & Shiferaw, B. (2013). Adoption of multiple sustainable agricultural practices in rural Ethiopia. Journal of Agricultural Economics, 64(3), 597-623.

Toulmin, C. (1986). Access to food, dry season strategies and household size amongst the Bambara of Central Mali. IDS Bulletin, 17(3), 58-66.

Udry, C. (1996). Gender, agricultural production, and the theory of the household. Journal of Political Economy, pp.1010-1046.

West, C. T. (2010). Household Extension and Fragmentation: Investigating the Socio-Environmental Dynamics of Mossi Domestic Transitions. Human Ecology 38.3, pp.363-376.

SUMMARY AND CONCLUDING REMARKS

Summary

This dissertation, organized in two studies, explores household structure and labor allocation in two different settings. The first part investigates labor allocation across plots within the same household among extended family members in rural Mali, where households are subject to production risk due to weather uncertainties. The second part examines labor allocation response to agricultural technology adoption, namely fertilizer microdosing, across households with differing family structure –that is, nuclear households versus extended households– in rural Burkina Faso.

In the first study, I develop a conceptual framework that describes how collective farming can be favored when households are exposed to production uncertainty due to high weather variability. In the empirical part, I use a two-wave plot level dataset collected in 2009 and 2012 and apply multiple levels of fixed effect and alternative functional forms and find strong empirical evidence that collective plots –managed by the heads of extended family households with output shared amongst all extended family members– are more intensively farmed with labor. To rule out the possibility that the longer time spent on the collective plots is not to satisfy nominal labor contribution on these plots, I also estimate crop yield performance and find that the higher labor allocation on the collective plots translates into higher crop yield performance, relative to that found on individual plots.[55] Findings also reveal that collective plots are more likely to receive more diverse sources of labor (i.e., labor from men, women, and children) relative to male individual plots.

I claim that the higher level of labor allocated to the collective plots can partly be explained as part of an ex-ante risk mitigation strategy against production uncertainty. To empirically test this claim, I investigate the labor allocation gap across collective and individual plots using the historical coefficient of variation of rainfall over twenty-seven years (1981-2007) as a proxy for production uncertainty. I find that

[55] Recall that individual plot managers are required to work on the collective plots before working on their own plots. Guirkinger and Platteau (2014) report complaints from the head of households about individuals tending to shirk on the collective plots to conserve their energy to work later on their own individual plots.

households living in villages with higher rainfall variability present a significantly higher labor allocation gap in favor of their collective plots relative to individual plots. Furthermore, using household level data, I find that nuclear households in places with higher historical rainfall variability are more likely to be engaged in collective farming. The results remain robust to the inclusion of household asset holdings and village-level covariates that may also be correlated with rainfall variability, providing strong suggestive evidence that collective farming may indeed constitute an ex-ante risk mitigation strategy among these households.

The second study uses randomized control trial (RCT) data combined with the difference-in-difference estimation method to investigate labor allocation response to the introduction of a specific fertilization technique, namely microdosing The program targeted rural subsistence sorghum growers in Burkina Faso for whom sorghum constitutes a major staple food, with the objective of improving sorghum productivity among these households and, consequently, increasing household food security.

The results show that while the intervention increased labor allocation to fertilizer application for sorghum production among all targeted households, its overall impact by household structure was starkly heterogeneous. To be precise, while the microdosing significantly increased labor allocation among nuclear family households, as expected given the labor-intensive nature of the technology, its overall impact on extended households was negative. Subsequent analyses disaggregated by specific agricultural tasks reveal that extended households substituted labor away from other sorghum production tasks to meet the additional labor needed to apply fertilizer, while there is no indication of such substitution effects among nuclear households. Furthermore, we find no evidence of labor substitution effects that diverted labor away from the production of other crops to sorghum production. Therefore, the findings imply that the microdosing technology induced an increase in the overall agricultural labor allocation for nuclear households.

One of the explanations we provide regarding the differential impact of the intervention relates to the fact that, like labor arrangements in Mali, individual plot managers in the extended households are required to work on the collective plots before working on their own individual plots. With this limited access to labor, non-head individual plot managers selected to receive the microdosing kit may not be able to acquire the additional labor required by the microdosing technique. This explanation appears to be sustained by the data as we find that recipients of microdosing kits who are household heads experienced a greater increase in labor allocated to fertilizer application, relative to non-head recipients.

Note that the gender differential aspect of the intervention has not been covered in this study as the paper focuses on nuclear versus extended family structures. Given the extent to which access to productive resources is strongly impacted by gender (see review by Quisumbing, 1996) while virtually all female-headed households are nuclear households, a consideration of gender would constitute a major confounding factor. Consequently, including gender would be a threat to the internal validity of the study. The gender question may constitute a separate research question on its own.

Concluding remarks

Taken together, these two studies emphasize the context specificity of labor allocation decision-making among subsistence farmers in West Africa. With respect to the first study, the theory on the production of collective goods would predict greater labor allocation on the individual plots due to moral hazard associated with the collective plots (Guirkinger and Platteau, 2015; Guirkinger and Platteau 2017). While I do not test for moral hazard in this study, the consistency of the higher labor allocation on the collective plots across different econometric specifications and sample restrictions strongly suggests that collective plots do not suffer from the issue of moral hazard.

One may argue that the guaranteed access to the output from collective plots may serve as a source of moral hazard on the individual plots. To be more precise, given the benefits of collective farming and knowing that the contribution of labor to collective plots allows nuclear households to share the production, individuals may be incentivized to minimize the labor allocated to their own plots. If this argument sustains, it would further support the claim that collective farming constitutes an insurance mechanism among these farmers. Otherwise, why would individuals be willing to provide more effort to the production of a collective good to the detriment of the production of a private good for which they are the sole claimants?

Regarding the labor response to the introduction of the microdosing technology in the second study, one would have expected a higher labor allocation response among extended family households, owing to their larger size, relative to nuclear family households. The findings from the two studies therefore seem contradictory at first glance. However, a close consideration of the nuances between labor allocation arrangements in the two studies shows the contextual specificity of each of them leading to three important considerations.

First, recall that the finding at the plot manager level in the second study reveals that recipients of the microdosing kits who are household heads experienced a higher increase in labor allocation devoted to fertilizer application relative to non-head recipients. If we assume that plots controlled by the head in the extended households are collective plots (as in Kazianga and Wahhaj, 2013, 2017), this finding would be in line with the results of the first study where I find that collective plots receive more labor relative to individual plots.

Second, in contrast to the first study, the nuclear households in the second paper, who experienced an increase in their labor response to the introduction of the technology, do not participate in collective farming. Several factors may explain the nonparticipation of these households in collective farming, including the possibility that they are self-sufficient regarding their labor needs. In addition, within the extended family households, multiple nuclear households coexist and must also allocate part of their labor endowment on their own individual plots within their nuclear household. In contrast, within the pure nuclear family household, there is only one head of household, which makes the latter more likely to have centralized control over labor endowment within the household. Consequently, he is more likely to be able to make workers more effectively respond to the labor requirement of the microdosing technology relative to the extended households where more units are involved in the production system.[56]

[56] Note that this argument does not contradict the claim that collective farming allows extended family members to apply a larger amount of labor with brute force when weather uncertainty leaves them with a small window of time to carry out some specific agricultural tasks. Weather uncertainty is historical and extended households can ex-ante put in place a labor arrangement system that allows them to deal with unpredictable weather outcomes. However,

Finally, nuclear households are the sole claimants of any potential increased output induced by the microdosing technology, in contrast to the extended households, where output is shared amongst members based on need rather than the contribution of effort (Guirkinger and Platteau, 2017; Kazianga and Wahhaj, 2013; 2017). As a result, nuclear households may have higher incentives to exert more effort in their sorghum production following the receipt of the microdosing kit, leading to a higher overall increase in their labor allocation relative to the extended family households.[57]

Combined with the demographic transition characterized by the increasing fragmentation of larger households into nuclear households in West Africa, this finding of positive labor response to the introduction of the microdosing suggests greater potentials for future agricultural technology diffusion. Whether these findings (that is, the positive response of labor among the nuclear households) imply focusing targeting efforts on this type of household structure for labor-intensive agricultural development interventions remains an open-ended question. The decisive answer to this question will ultimately depend on the objective and the ethical issues surrounding the motives for such interventions.

It is important to highlight that the current work does not claim that collective farming among extended family members is ineffective, *per se*, especially given the beneficial features of collective farming described in the first paper. Rather, paper points out the central role played by human labor as a productive resource among small-scale subsistence farmers and how its limited availability may have implications for agricultural intensification. Though the issue of labor constraints among small scale subsistence farmers has been extensively explored in the existing empirical literature, the current work brings important insights. Specifically, it both reinforces the importance of a consistent household

the introduction of the microdosing technology brings a different nature of labor coordination, as it comes with specific embodied recommendations.

[57] Note that this potential difference in incentives does not contradict the claim that nuclear household members have an incentive to diligently work on the collective plots in the first study in the case of Mali. There, the claim is that nuclear households engage in collective farming to overcome labor bottlenecks when production uncertainties prevail due to weather variability. In the case of the microdosing in Burkina Faso, the nuclear households operate in 'autarky' and may be less labor constrained. Note that nuclear households operating in 'autarky' also exist among the studied population in Mali. However, they are not covered in that study because the objective of the empirical investigation there is to look at differences in labor allocation across plots within the same household.

definition for successful targeting in social program interventions (Beaman and Dillon, 2012), and it illustrates how the dynamics in household labor allocation decision making can be complex, context-specific and highly dependent on the structure of the household. This highlights the challenges faced by development practitioners to replicate development programs aiming at alleviating these labor constraints at large scales, which underscores the need for an improved understanding of rural household economies.

REFERENCES

REFERENCES

Beaman, L., & Dillon, A. (2012). Do household definitions matter in survey design? Results from a randomized survey experiment in Mali. Journal of Development Economics, 98(1), 124-135.

Guirkinger, C., Platteau, J. P., & Goetghebuer, T. (2015). Productive inefficiency in extended agricultural households: Evidence from Mali. Journal of Development Economics, 116, 17-27.

Guirkinger, C., & Platteau, J. P. (2017). Transformation of African Farm Households: A Short Survey of Economic Contributions. Journal of Demographic Economics, 83(1), 41-50.

Kazianga, H., & Wahhaj, Z. (2013). Gender, Social Norms, and Household Production in Burkina Faso. Economic Development and Cultural Change, 61(3), 539-576.

Kazianga, H., & Wahhaj, Z. (2017). Intra-household resource allocation and familialties. Journal of Development Economics, 127, 109-132.

Quisumbing, A. R. (1996). Male-female differences in agricultural productivity: Methodological issues and empirical evidence. World Development, 24(10), 1579-1595.

West, C. T. (2010). Household extension and fragmentation: Investigating the socio-environmental dynamics of Mossi domestic transitions. Human ecology, 38(3), 363-376.