

Aus dem Institut für Agrarökonomie
der Christian-Albrechts-Universität zu Kiel

**Socioeconomic Assessments of Organic Fertilizer Use among Smallholder Farmers in
Northern Ghana**

Dissertation
zur Erlangung des Doktorgrades
der Agrar- und Ernährungswissenschaftlichen Fakultät
der Christian-Albrechts-Universität zu Kiel
vorgelegt von

M.Sc. Bunbom Edward Daadi

aus (Nyinahin, Ghana)

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Dedication

To my dear family

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Bunbom Edward Daadi

Table of Contents

List of Tables	x
List of Figure	xii
Abstract in English	xiii
Abstract in German	xv
Chapter 1: General Introduction	1
1.1 Background	1
1.2 Significance of the Study	3
1.3 Agriculture, soil degradation, and organic fertilizer use in northern Ghana	5
1.4 Study area, sampling and the sample	6
1.5 Structure of the thesis	8
References	9
Chapter 2: Organic fertilizer use by smallholder farmers: typology of management approaches in Northern Ghana	15
Abstract	15
2.1 Introduction	16
2.2 Organic soil amendment in northern Ghana	18
2.3 Methodology	20
2.3.1 Common tools for typological studies	20
2.3.2 Conceptual framework	21
2.3.3 Data and description of variables	23
2.3.4 Empirical EFA model and procedure	26
2.3.5 Characterization using seemingly unrelated regression (SUR) analysis	28
2.4 Results and discussion	30
2.4.1 Identification of OFM approaches	30
2.4.2 Characteristics of OFM approaches	34
2.5 Conclusion and recommendations	39
References	40
Chapter 3: Organic fertilizer practices and Farmers' attitude in Northern Ghana: empirical insights using the attitude-as-behavior model	47
Abstract	47
3.1 Introduction	48
3.2 Farmer attitude assessment: Shifting from classical to behavioral approach	50

3.3 Methodology	53
3.3.1 The concept of attitude-as-behavior (Behavioral Approach)	53
3.3.2 Rasch model specification	55
3.3.3 Data and descriptive statistics	57
3.4 Results and Discussion	59
3.4.1 Rasch measurement model and fit indexes	59
3.4.2 Explanatory (Latent regression) model results	61
3.4.3 OFP difficulty of and farmer attitude measures	61
3.4.4 Determinants of organic fertilizer attitudes	63
3.5 Conclusions and recommendations	65
References	67
Appendices 3	73
Chapter 4: Organic Fertilizer Adoption, Household Food Access, and Gender-based Farm Labor Use: Evidence from Northern Ghana	74
Abstract	74
4.1 Introduction	75
4.2 Organic fertilizer use in Northeastern Ghana	78
4.3 Methodology	79
4.3.1 Sampling, data and measurements	79
4.3.2 Theoretical model	80
4.3.3 Empirical specification of endogenous switching regression model	82
4.4 Empirical Results and discussion	85
4.4.1 Data summary statistics	85
4.4.2 Drivers of organic fertilizer adoption	87
4.4.3 Factors explaining household food expenditure, food gap and labor use	90
4.4.4 Effects of organic fertilizer use on food security and labor demand	93
4.4.5 Organic fertilizer effect heterogeneity	96
4.5 Summary and Conclusions	97
References	98
Appendices 4	105
Chapter 5: Composting Waste for Agriculture in Northern Ghana: Rural Farmers' Willingness to Pay for Essential Attributes	106
Abstract	106
5.1 Introduction	107

5.2 Methodology	109
5.2.1 Survey development, discrete choice experiment and farmer Characteristics	109
5.2.2 Conceptual framework and econometric model	114
5.3 Empirical Results	118
5.3.1 G-MNL Model Results	118
5.3.2 Attributes preference heterogeneity and indicators	121
5.3.3 Farmers' Willingness-to-pay for MSW compost attributes	123
5.4 Discussion and conclusion	125
References	127
Chapter 6: Conclusions and policy recommendations	131
6.1 Summary of empirical methods	131
6.2 Summary of findings	132
6.3 Policy implications and recommendations	133
Appendices	135
Appendix 1: Questionnaire	135
Appendix 2: Curriculum vitae	153

List of Tables

Table 1.1: Distribution of sample respondents by location	8
Table 2.1: OFM decision/practice variables used in EFA to identify OFM approaches	24
Table 2.2: Farmer/plot variables used in SUR characterization model	26
Table 2.3: Eigenvalues of initial factors	31
Table 2.4: Rotated factor pattern of loadings on variables of OFM approaches	32
Table 2.5: SUR model estimates of characteristics of OFM approaches	36
Table 2.6: Percentage spatial distribution of OFM practices by farm location	38
Table 3.1: Farmer/farm characteristic factors summary statistics	57
Table 3.2: Description and summary of organic fertilizer practices in attitude instrument	58
Table 3.3: Difficulty (δ) estimates of practices by descriptive Rasch measurement model	59
Table 3.4: Generalized linear and latent mixed model estimates for DML and EML Rasch models	62
Appendix 3B: Initial output from Factor analysis of OFPs to determine attitude dimension	73
Table 4.1: Summary statistics of variables	86
Table 4.2: First-stage FIML estimates of organic fertilizer adoption probit model	89
Table 4.3: ESR estimates of determinants of household food access and labor used	92
Table 4.4. ESR-based average expected outcomes; treatment and heterogeneity Effects	94
Appendix 4A: Distribution of sample households in the study area	105
Appendix 4B: Box-cox model specification test	105
Appendix 4C: Falsification test of exclusion variable	105
Appendix 4D: Endogenous treatment effect (eteffects) model-based adoption effects	105
Table 5.1: Compost attributes and levels in choice experiment	111
Table 5.2: Example of choice sets presented to farmers to elicit preferences	113
Table 5.3: Major socioeconomic characteristics of sample farmers	113

Table 5.4: G-MNL estimates of compost bag choice models	119
Table 5.5: Scale heterogeneity in mean parameter model estimates	122
Table 5.6: Willingness to pay for compost attributes in willingness-to-pay space	124

List of Figures

Figure 1.1: Map of Ghana in Africa, identifying the study location	7
Figure 2.1: Smallholder-farmers' decision framework of managing soil nutrients	22
Figure 3.1: Structural representation of Rasch model in a GLMM	54
Figure 3.2: Distribution of respondents' scores and odd-Ratios of practice	63
Figure 3.3: Farmers' infit and outfit indexes for Rasch measurement model	60
Figure 3.4: Farmers-practices map on Rasch scale	60
Figure 3.5: Distribution of expected a posteriori (EAP) farmer attitude scores	63
Appendix 3A: Distribution of farmers' scores and odd-Ratio of practices	73
Appendix 3C: Screeplot test of eigenvalues against respective factors	73
Figure 4.1: Kernel density distribution of outcome variables by adoption status	87
Figure 4.2: Scatter plots of adoption effects with polynomial lines by adoption status	96
Figure.5.1: Marginal probabilities of uptake with attributes and level changes	121
Figure 5.2: Distributions of farmer-specific WTP for MSW compost attributes	125

Abstract

Food insecurity and poverty continue to be major challenges for human development in Sub-Saharan Africa due to low agricultural productivity, linked to deteriorating soil conditions and inappropriate agrarian technologies. Green revolutionary measures, particularly increasing mineral fertilizer application, have always been proposed as natural remedies for resolving the yield crisis. However, Sub-Saharan African farmers face a myriad of challenges regarding mineral fertilizer use amid poorly developed input markets. Moreover, recent advances made towards fertilizer access in countries like Ghana have shown that merely increasing mineral fertilizer application is no panacea to African's farm productivity crisis, where arable lands have degraded. Meanwhile, organic fertilizers play a significant role in improving soil conditions for effective mineral fertilizer use. Thus, the focus on fertilizer use has shifted towards combining mineral with organic fertilizers for improved soil health and productivity. Towards this goal, agricultural development agencies in Northern Ghana, for the past decade, have been priming farmers to access and use more organic fertilizers, but the input's use remains low for many reasons, including a general lack of biomass in the area. This study explored rural farmers' motivations, decisions and behaviors regarding organic fertilizer use in the northeastern part of Ghana. It thus contributes insights from farmers' perspectives to the growing literature on organic-inorganic fertilizer use debate in Sub-Saharan Africa. Specifically, the study first examined observed farmer-decisions to identify decision trajectories (management approaches) that lead rural farm households to organic fertilizer use and related the decision classes to farmers' socioeconomic factors, including farm-resource base, using seemingly unrelated regressions to adjust for correlations between decisions. Second, it evaluated behavioral costs (difficulty) associated with prevailing organic practices and scaled farmers' attitudes towards organic fertilizer use, using the explanatory Rasch model to account for influences of farmer-characteristic difference on the scale. Third, following the potential outcome framework, an endogenous switching regression is employed to control for observed and unobserved organic fertilizer use selectivity as well as endogeneity biases while examining the input's effects on per capita food expenditure, food gap, and farm labor use. The final part of the study evaluated the possibility for municipal solid waste compost producers to market their products to rural farmers in Northern Ghana. Applying the generalized multinomial logit model on choice experimental data, the study account for preference and scale-heterogeneity and estimated farmers' willingness to pay for attributes of a hypothetical municipal waste compost. The typological analysis revealed four management approaches (decision trajectories) among the farmers. Three of these are borne by strategic motivations and actions, which, if supported, could lead to a significant increase in organic fertilizer use by the farmers. The seemingly unrelated regression analysis showed that uptake of each approach is affected by a subset of farmer characteristics. However, all include participation in training on organic fertilizer management. The empirical results also show that organic fertilizer practices in the area are generally moderate in behavioral difficulty. However, most of the farmers have weak attitudes; hence, they cannot effectively exploit over 80% of the practices. This attitude weakness is strongly related to farmers' socioeconomic factors, including low education and poor farm resource base. Despite the weak attitudes, the study further revealed that organic fertilizer significantly increases food consumption and reduces seasonal food-shortage in households who are able to use it. However, it requires more farm labor use, with nearly all the increased labor

burden borne by female farmhands. Finally, the study has proven that, though with varied preferences, compost attributes, including its form, packaging (brand/label), and access, influence rural farmers' decision to buy it. The findings have significant policy implications. Particularly, they call for interventions that mitigate farmer-background factors hindering organic fertilizer adoption. Educating farmers through soil fertility management training, and helping them, especially females, acquire draught equipment are critical to increasing organic fertilizer use. Lastly, the government should subsidize organic fertilizers more than 50% to cover distribution costs, such that dealers can make it physically accessible to rural farmers.

Zusammenfassung

Ernährungsunsicherheit und Armut sind aufgrund der geringen landwirtschaftlichen Produktivität, die mit sich verschlechternden Bodenbedingungen und unangemessenen Agrartechnologien verbunden ist, weiterhin große Herausforderungen für die menschliche Entwicklung in Subsahara-Afrika. Maßnahmen der „grünen Revolution“, insbesondere die Erhöhung des Einsatzes von Mineraldünger, waren schon immer das vorgeschlagene natürliche Heilmittel zur Lösung der Ertragskrise. Landwirte in dieser Region stehen jedoch vor einer Vielzahl von Herausforderungen hinsichtlich des Einsatzes von Mineraldünger in schlecht entwickelten Inputmärkten. Darüber hinaus haben die jüngsten Fortschritte beim Zugang zu Düngemitteln in Ländern wie Ghana gezeigt, dass die bloße Erhöhung des Einsatzes von Mineraldünger kein Allheilmittel für die Krise der landwirtschaftlichen Produktivität in Afrika ist, in der die Qualität des Ackerlandes abgenommen hat. In der Zwischenzeit spielen organische Düngemittel eine wichtige Rolle bei der Verbesserung der Bodenbedingungen für eine effektive Verwendung von Mineraldüngern. Daher hat sich der Fokus auf die Verwendung von Düngemitteln auf die Kombination von Mineraldüngern mit organischen Düngemitteln verlagert, um die Gesundheit und Produktivität des Bodens zu verbessern. Um dieses Ziel zu erreichen, haben landwirtschaftliche Entwicklungsagenturen in Nordghana die Landwirte in den letzten zehn Jahren darauf vorbereitet, Zugang zu mehr organischen Düngemitteln zu erhalten und diese zu verwenden. Der Einsatz dieses Inputs bleibt jedoch aus verschiedenen Gründen gering, unter anderem wegen des allgemeinen Mangels an Biomasse in der Region. Diese Studie untersuchte die Motivationen, Entscheidungen und Verhaltensweisen der Landwirte in Bezug auf die Verwendung von organischem Dünger im Nordosten Ghanas. Damit werden Erkenntnisse aus Sicht der Landwirte in die wachsende Literatur zur Debatte über die Verwendung von organisch-anorganischen Düngemitteln in Afrika südlich der Sahara eingebracht. In der Studie wurden zunächst beobachtete Entscheidungen von Landwirten untersucht, um Entscheidungspfade (Managementansätze) zu ermitteln, die landwirtschaftliche Haushalte zum Einsatz von organischem Dünger führen. Anschließend wurden die Entscheidungsklassen mit den sozioökonomischen Faktoren der Landwirte, einschließlich der Ressourcenbasis der landwirtschaftlichen Betriebe, in Beziehung gesetzt, wobei scheinbar nicht verwandte Regressionen (SUR) verwendet wurden, um Korrelationen zwischen Entscheidungen auszugleichen. Zweitens wurden die Verhaltenskosten (Schwierigkeiten) im Zusammenhang mit der Anwendung organischer Praktiken sowie die Haltung der Landwirte gegenüber organischer Düngung mit Hilfe eines Rasch-Modells analysiert. Drittens wird gemäß dem Rahmen für potenzielle Ergebnisse eine endogene Umschaltregression angewendet, um die beobachtete und unbeobachtete Selektivität des Einsatzes organischer Düngemittel sowie die Verzerrung durch Endogenität zu kontrollieren und gleichzeitig die Auswirkungen des Inputs auf die Pro-Kopf-Nahrungsmittelausgaben, die Nahrungslücke und den Einsatz landwirtschaftlicher Arbeitskräfte zu untersuchen. Im letzten Teil der Studie wurde die Möglichkeit bewertet, dass Produzenten von Kompost, der aus Siedlungsabfällen gewonnen wird, ihr Produkt an die Landwirte vermarkten. Dazu wurde unter Verwendung des G-MNL-Modells (Generalized Multinomial Logit) mit Daten von Auswahlexperimenten die Zahlungsbereitschaft der Landwirte für Kompost geschätzt. Durch das verwendete G-MNL-Modell wurden die Heterogenität der Präferenzen sowie Skalenheterogenität berücksichtigt. Die typologische Analyse ergab vier Managementansätze

(Trajektorien von Entscheidungen über organische Düngemittel) bei den Landwirten. Drei davon werden von strategischen Motivationen und Maßnahmen getragen, die zu einem signifikanten Anstieg des Einsatzes von organischem Dünger führen könnten. Die SUR-Analyse ergab, dass die Akzeptanz jedes Ansatzes von einer Untergruppe von Merkmalen der Landwirte beeinflusst wird, alle umfassen jedoch die Teilnahme an Schulungen zum Management von organischen Düngemitteln. Die empirischen Ergebnisse zeigen weiterhin, dass die Landwirte in der Untersuchungsregion die mit der Anwendung organischer Düngemitteln verbundenen Schwierigkeiten im Allgemeinen als moderat einschätzen. Die Mehrheit der Landwirte hat jedoch eine schwache Einstellung. Daher können sie nicht mehr als 80% der organischen Düngungspraktiken effektiv ausnutzen. Diese Einstellungsschwäche hängt mit den sozioökonomischen Faktoren der Landwirte zusammen, darunter geringer Bildungsstand und eine zu geringe Faktorausstattung. Trotz der schwachen Einstellungen ergab die Studie weiter, dass der Einsatz organischer Dünger den Lebensmittelkonsum signifikant erhöht und die saisonale Nahrungsmittelknappheit in den Haushalten verringert. Dies erfordert jedoch einen signifikant höheren Arbeitseinsatz, wobei fast die gesamte erhöhte Arbeitsbelastung von Frauen getragen wird. Schließlich hat die Studie bewiesen, dass MSW-Kompostattribute, einschließlich Form, Verpackung (Marke/Etikett) und Marktzugang, trotz unterschiedlicher Präferenzen für die Kaufentscheidung der Landwirte von entscheidender Bedeutung sind. Aus den Ergebnisse ergeben sich politische Implikationen. Um die Verbreitung organischer Düngemittel voranzubringen, sollten die Faktoren, welche die Einführung organischer Düngemittel behindern, abgeschwächt werden. Dazu gehören insbesondere die Aufklärung der Landwirte durch Schulungen zum Bodenfruchtbarkeitsmanagement und die Unterstützung insbesondere von Frauen beim Erwerb von Zuggeräten. Schließlich sollte die Regierung organische Düngemittel zu mehr als 50% subventionieren, um die Vertriebskosten zu decken, damit die Händler sie den Landwirten physisch zugänglich machen können.

Chapter 1

General Introduction

1.1 Background

Food insecurity and poverty are major challenges in Sub-Saharan Africa (SSA) due to low agricultural productivity caused by poor soil health and inappropriate farming technologies (AfDB, 2006; and Nkonya *et al.*, 2016). While the region's population is rapidly growing, crop production and yields decline because of deteriorating soil conditions (Waithaka *et al.*, 2007; Tittonell and Giller, 2013; and Nkonya *et al.*, 2016). Land scarcity and related constraints limit crop production, accelerate soil nutrient depletion, and reduce fallowing for replacing lost nutrients. These result in severe soil nutrient imbalances affecting crop yields (AfDB, 2006; Shisanya *et al.*, 2009; Awoonor 2012; Tittonell and Giller, 2013; Kassie *et al.*, 2013; FAO, 2015; Vanlauwe, 2015; and Martey, 2018). Since soil fertility basically predicts yields and, thus, incomes of farm households, the food insecurity and poverty situation in SSA is intricately linked to soil conditions (Tittonell and Giller, 2013; and Kim and Bevis, 2019).

Increasing mineral fertilizer use has been the proposed natural remedy to African farmers' low crop productivity (Vanlauwe, 2015). However, SSA countries face considerable challenges in accessing mineral fertilizers amid poorly developed input markets (Liverpool-Tasie *et al.*, 2017; and Sheahan and Barrett, 2017). Economic-wise, fertilizers are expensive imports to SSA. Increasing the import under a government fertilizer subsidy program increases public expenditure and, consequently, foreign exchange deficits. Despite government subsidies, mineral fertilizer is still relatively costly for an average African farm household to acquire without compromising some consumption needs (Zingore *et al.*, 2007; and Sheahan and Barrett, 2017;).

Furthermore, physical access limitations in remote areas often impede the timely procurement of the input to ensure effective use for increased outputs (Vanlauwe, 2015 and Thelma *et al.*, 2017). Where farmers have reliable access, usually, the same form of mineral fertilizer is available. Thus, farmers have applied these formulations every season without any soil test-based recommendation. Currently, shreds of scientific evidence pointing to soil acidity and structural damages are emerging in some areas (e.g., Atakora *et al.*, 2014). This means that farmers cannot continue to rely solely on mineral fertilizer to sustain crop yields.

Meanwhile, agricultural and environmental benefits associated with organic fertilizer use are well known and documented (MoFA, 2013). Organic fertilizers support production systems by maintaining biodiversity and soil carbon-cycle (IFOAM, 2004; Auerbach *et al.*, 2013; Rajendran

et al., 2016; and Sudradjat *et al.*, 2018). They also help conserve soil nutrients and water by reducing leaching, allowing crops to utilize nutrients efficiently, even under arid conditions. Consequently, organic fertilizers have proven to maintain yields under drought conditions (Pimetel *et al.* 2005 and CalCAN, 2011).

Traditionally, smallholder farmers have used manure on their grain fields to supplement insufficient mineral fertilizers or only manure when they have no mineral fertilizer (Powell *et al.*, 1993). But the eco-friendly roles of organic fertilizers noted above make it complementary to mineral fertilizers; hence, the need to use them together (Usman *et al.*, 2015; and Vanlauwe, 2015). In recent times, the role of organic fertilizer in water conservation in adapting crop systems to shocks as increasing weather variability continues to threaten the frail production systems has become prominent in Sub-Saharan Africa (Amikuzino and Donkoh, 2012). Particularly in northern Ghana, where rainfall in the country is most erratic, farmers are being encouraged to use organic fertilizer as a water-smart soil amendment to help crops withstand frequent dry spells (Bandanaa *et al.*, 2016; Kuwornu *et al.*, 2017; and Issahaku and Abdulai, 2019).

However, adopting organic fertilizers also appears challenging to farmers in rural northern Ghana. The input is currently not on the market to be bought, meaning that farmers must produce it or arrange to secure it from sources where readily useable forms exist. Yet, there is a general lack of required materials due to low vegetative cover and competing uses of the little biomass in the area. It is difficult for farmers to source enough quantities of the input; thus, the rate at which they use it has not been impressive (GIZ, 2013; Tittonell and Giller, 2013; Vanlauwe, 2015 and Wekesah *et al.*, 2019).

Another reason for the growing importance of organic fertilizer in Ghana is the prospects it has in dealing with urban waste menace (Pradhan *et al.*, 2013) and reducing greenhouse gas (GHG) emissions through composting (Galgani *et al.*, 2014; UNFCCC, 2015; and Republic of Ghana, 2015). Composting municipal solid waste (MSW) for agricultural use also closes the soil nutrient-cycle from urban waste to rural farmlands (Danso *et al.*, 2006, 2017). For MSW composting to affect these goals, the sector must be well commercialized to produce significant quantities, with effective marketing channels to supply rural farmers. Unfortunately, MSW compost in Ghana has remained very limited in supply and available to only city gardeners and peri-urban farmers. Meanwhile, instead of exploring the possibility of extending the market to rural farmers, studies (e.g., Danso *et al.* 2002, 2006, 2017; Pradhan *et al.*, 2013; Kuwornu *et al.*, 2017) on prospects of the sector in sustainable waste management have focused on compost demand among urban

consumers, thus blaming the supply limits on low demand and high cost of distributing the input to distanced areas.

This study focuses on farmers' decisions to use organic fertilizer in relation to socioeconomic and farming-context factors influencing such decisions as well as their effects on farm households in SSA. Specifically, the study examines farm-households' motivations, decisions, and behaviors to identify management trajectories leading to organic fertilizer use, using observed organic fertilizer decisions of rural farmers in northeastern Ghana as a case. It evaluates the difficulty of organic fertilizer practices against farmers' general attitude towards using the input. After that, the effects of organic fertilizer adoption on farm household's welfare are evaluated. Given that rural farmers cannot produce sufficient quantities of the input for use, the final part of the study examines their potential demand for compost through analysis of willingness-to-pay, using a hypothetical MSW compost from Tamale.

1.2 Significance of the Study

While agricultural production is predicted to decline in SSA due to competing land usage, climate change, and soil degradation, food supply has to increase by 70% before 2050 if serious food security challenges are to be avoided. This calls for policies to support farmers' adaptation to climate shocks and soil depletion to maintain production and productivity in the region (FAO, 2010). For that purpose, helping farmers use organic fertilizers to conserve soil and water is one practicable adaptation policy to consider. Designing an effective policy for organic fertilizer support requires empirical information about existing practices regarding the input's use among target farmers. However, such information is currently lacking, particularly in northern Ghana. The organic fertilizer adoption literature is very silent concerning pragmatic decisions smallholder farmers make to procure the input for use. This study contributes towards filling the information gap by adopting Mowo *et al.*'s (2006) farmer-decision framework to observe and identify typologies of existing organic fertilizer use decisions/practices among rural farmers in northern Ghana.

The push for farmers to increase organic fertilizer use will succeed if it supports organic practices that match farmers' behavioral inclination (attitudes) and decision-making capacity (Lagerkvist *et al.*, 2015 and Shikuku *et al.*, 2017). Attempt to promote organic fertilizer use without understanding why farmers do not exploit existing practices to utilize the input tends to mislead policy efforts (Martey, 2018). An intuitive way to gain such insights is to match farmers' behavioral disposition against behavioral costs (difficulties) of adopting the existing/intended

practices (Durpoix, 2010). Unfortunately, there has not been any empirical evaluation of behavioral costs or farmers' behavioral inclination towards organic fertilizer practices being promoted, particularly in Ghana. Against this backdrop, this study fills yet another information gap by providing the first empirical estimates of the behavioral cost associated with prevailing organic fertilizer practices and farmers' behavioral inclination towards the practices.

Though the literature (e.g., Kassie *et al.*, 2009; Usman *et al.*, 2015; Gelgo *et al.*, 2016; Zerihun and Haile, 2017; and Abebe and Debebe, 2019) provides evidence attesting to positive impacts of organic fertilizer on farm productivity and thus, the general welfare of farmers, specific evidence regarding food access is fuzzy, whereas that about farm labor use is nonexistent. Notably, in Ghana, Martey (2018) examined the effects of organic fertilizer on crop productivity, household incomes, poverty, total expenditure, and food consumption expenditure. The study found that adoption increased crop productivity, incomes, and total expenditure but reduced poverty and food consumption expenditure in farm households. The welfare indexes examined by these previous studies capture overall food access status without reference to the stability dimension. Yet, that dimension of food access is critical to food security of farm-households as dual economic agents. Besides, organic fertilizer adoption is expected to occur at the cost of other input adjustments, especially labor (Fuglie and Bosch, 1995). Potential increases in labor requirements could be a hindrance to adoption and the associated benefits to farmers. However, to the best of our knowledge, the extent to which organic fertilizer adoption affects farm labor use in SSA has not been empirically examined. These underscore the need for studies to inform organic fertilizer adoption policies. Thus, this study, which evaluates the effects of organic fertilizer on household food stability as well as on labor use among rural farmers, becomes significant.

Furthermore, linking agriculture to MSW compost production is noted as a critical path to closing the rural-urban nutrient-cycle while sustainably dealing with sanitation challenges in African cities (Danso *et al.*, 2002; 2006; 2017; Pradhan *et al.*, 2013 and Agyekum *et al.*, 2014). This requires a compost market with substantial demand to drive commercialization of the MSW production sector to a composting level that achieves these twin purposes. Good market potentials exist among rural farmers for expanding demand (Folefack, 2008). Yet, the input's supply has remained limited to city gardeners and peri-urban users. While rural smallholder crop farmers do not have physical access to the input and try to produce alternatives on their own, studies trying to understand MSW compost demand have, so far, focused on the consumers that are in close proximity of compost stations. Except for Folefack (2008), no study has considered rural farmers' perspectives in understanding commercial compost demand, particularly in Ghana.

1.3 Agriculture, soil degradation, and organic fertilizer use in northern Ghana

A vibrant agricultural sector is fundamental to the economic development of northern Ghana. The area has a predominantly agrarian employment structure with meager income earning capacity. Food crop farming is the primary source of livelihood for over 74 percent of the working population (Government of Ghana, 2015). However, the earnings from the occupations are low due to poor agricultural practices besides low soil fertility and the total dependence on erratic rainfall, resulting in poor farm productivity (Armah 2011; Wiredu, 2015; GSS, 2015).

The North East and Upper East regions have the densest farming populations, working on the poorest farmlands, under the most unpredictable weather conditions in northern Ghana (Issahaku *et al.*, 2016). Semi-arid situations coupled with intensive and continuous cropping without proper nutrient replacement have degraded most farmlands (Amikuzonu and Donkor, 2012 and Government of Ghana, 2015). Thus cereal production in those regions has increasingly become mineral fertilizer dependent, absorbing the largest chunk of mineral fertilizers consumed in northern Ghana (FAO, 2005). Farmers increase fertilizer application consistently above the national rate since the introduction of the fertilizer subsidy program in 2008 (Wiredu, 2015). However, yields are declining and agronomists warn that continuous use of existing fertilizer formulations without balancing with organic carbon damages soil properties and renders farmland non-responsive to further mineral fertilizer increases (Atakora *et al.*, 2014).

A natural option for the farmers to adapt their farming systems to weather shocks and soil depletion, where irrigation and drought-resistant crop varieties are absent, is to adopt organic fertilizer to conserve soil and water (FAO, 2013 and Bandanaa *et al.*, 2016). In this regard, the Ministry of Food and Agriculture (MoFA), in partnership with several not-for-profit agencies, has at different times during the past decades implemented projects to support farmers in the area to adopt organic fertilizer (Bandanaa *et al.*, 2016). The general purposes were to increase the quantity and quality of organic amendments farmers use and improve the efficiency of its application by modernizing farmers' traditional practices (Bellwood-Howard, 2013). The not-for-profit organizations, such as the Presbyterian Agriculture Station (PAS) and Opportunity for Industrialization Center (OIC), have trained farmers on pit and heap methods of compost preparation. They have also supported some farmer-groups to acquire draught equipment (donkey carts) for gathering organic materials (Bellwood-Howard, 2013). Agricultural Cooperative Development International/Volunteers in Overseas Cooperative Assistance (ACDI/VOCA) and Alliance for Green Revolution in Africa (AGRA) have also primed farmers on efficient methods

of applying the input, such as the *Zai-pit*¹ method and micro-dosing crops with mineral fertilizers. A contractual relationship between some farmers and itinerant Fulani herdsmen to temporary kraal livestock on cereal plots to accumulate manure before cropping has also become a traditional practice in the area, following the agencies' programs.

1.4 Study area, sampling, and the sample

Specifically, this study was carried out within the two northeastern (North East and Upper East) regions of Ghana. The area lies across the Guinea and Sudan Savannah agro-ecological zones, both of which experience a unimodal rainfall pattern, with annual average precipitation between 1000 to 1100 mm. The topography is generally undulating with many hilly and rocky areas (MoFA, 2012). The soil is either sandy or clayey and shallow in topsoil with very low organic matter content due to low vegetative cover and rocky nature of the area. The sandy soil, coupled with slopy topography, accelerates erosion during heavy rainfall. The clayey lands, usually in valleys, are most fertile but easily become flooded following downpours (Fagariba *et al.*, 2018). The figure below (Figure 1.1) shows the study location covering the North East, Upper East regions, and some parts of the Northern Region.

The area was chosen for the study because its farm population is most vulnerable to soil fertility crises and weather variability in Ghana. Thus, efforts to adapt by using organic fertilizer have been relatively pronounced. The area has dense rural settlement clusters, constituting more than 74% of the total population, around three main urban centers (i.e., Bolgatanga, Bawku, and Bunkpurugu). About 90% of the rural households depend primarily on agricultural activities for a living. Small-scale food crop production, mainly grains like sorghum, millet, and maize, is the households' mainstay economic activity, with generally low productivity (MoFA, 2017 and Republic of Ghana, 2015).

¹ Zai is a term that refers to small planting pits that typically measure 20-30cm wide, 10-20cm deep and spaced 60- 80cm apart. It is a technique used to rehabilitate degraded drylands with hard pans and to restore soil health. The pits break through soil pan and collects and conserves water and organic matter which supports crop growth and in the long-run, help soften and gradually break the entire soil (Danquah *et al.*, 2019).



Figure 1.1. Map of Ghana in Africa, identifying the study location

In recent times, farmers cannot maintain production because of land degradation and declining farm sizes (Awoonor 2012; and Amikuzonu and Donkor, 2017). Yields also continue to decrease because of increasing weather variability with the resultant rainfall-related shocks and the growing rates of soil nutrient mining (Martey *et al.*, 2014; Ndamani and Watanabe, 2013; and Amikuzonu and Donkor, 2017). Therefore, farmers in the area need to adapt their practices in order to cope with the effects of the changing farm conditions.

For this reason, the farmers are being encouraged to apply organic soil amendments to improve and sustain soil health. Three farm-technology transfer centers, operated by the Presbyterian Agriculture Station (PAS), are located within the area: Langbinsi, Garu, and Sandema. This study chose to draw its sample farmers along the operational areas of the farm-technology transfer

centers because of the extension services they have provided to farmers on sustainable agriculture. Many farmers have benefited from interventions on sustainable soil management practices, including training on organic compost preparation and application. Thus, organic fertilizer adoption by farmers in the area approximates a quasi-experiment driven mainly by individual farmer/farming context factors.

A multi-stage sampling procedure was applied to obtain respondents for the survey. The first stage involved a purposive delineating of the farm population into four clusters. Three clusters comprise farming communities around Langbinsi and Garu PAS, while the fourth cluster (around Bunkpurugu), on the contrary, is located beyond a 50-kilometer radius of any PAS center and has no farm-technology center within. Communities within clusters were randomly selected using lists obtained from the technology centers and MoFA district office at Bunkpurugu. With assistance from farmer-group and opinion leaders at the community level, we compiled a list of households as a sampling frame for the final stage random selection of respondents. At the end of the survey, 250 respondents used organic fertilizer on their cereal plots for the 2017/18 crop, while 262 respondents did not, constituting a total sample of 512 farmers for this study. Table 1.2 shows the distribution of sampled communities and households by organic fertilizer use regimes across the study clusters. However, depending on the specific objectives and missing data points in variables involved, various the analysis for the various chapters used different sample sizes.

Table 1.1: Distribution of sample respondents by location

Zone	Number of Communities	Organic Users	Non-organic Users	Total
Langbinsi Area	14	61	70	131
Garu West (Manga Area)	13	58	65	123
Garu East (Tempane-Pusiga Area)	13	75	82	157
Bunkpurugu Area	12	56	45	101
Study Area	52	250	262	512

1.5 Structure of the thesis

This thesis is a collection of research articles organized into six chapters as follows. The next chapter (chapter 2) is an exploratory study that examines fertilizer use decisions among rural smallholder farmers. It applies exploratory factor analysis, followed by a seemingly unrelated regression model, to identify and characterize management strategies. To the extent that policy planning requires information on existing practices under specific farming conditions, the study's results provide an essential basis for designing targeted organic fertilizer policies. The entire chapter is based on a paper that has been published in *Renewable Agriculture and Food Systems* (Daadi and Latacz-Lohmann, 2020)

Chapter 3 focuses on scaling farmers' attitudes to organic fertilizer relative to the psychological difficulties of a set of common practices towards organic fertilizer adoption. It applies the explanatory Rasch model to evaluate both difficulty of organic practices and farmers' attitudes on a logit scale. The model controls for effects of farmers' characteristic differences on attitudes in order to obtain objective difficulty estimates for the practices. This allows matching of farmers' attitude levels against difficulties of practices to identify practices for which farmers require external support to adopt. A paper from this chapter has been submitted to *Helyon: agriculture section*.

Chapter 4 evaluates and presents empirical evidence of the effects of organic fertilizer on farm-household welfare through food security and labor requirement. Due to the close links with farm household food security, per-capita food consumption and food gap (food-deficit) indexes, as well as female and male labor workdays, are examined. The nature of organic fertilizer adoption and the rural farming context under study approximate a natural experiment. Organic fertilizer adoption is endogeneous in the setup, while adopters differ from non-adopter, both in their observed and unobserved characteristics. To account for this bias, the potential outcome framework, using endogenous switching regression (ESR), is applied to examine the determinants of adoption while modeling outcomes for the separate adoption regimes. Thus, the average treatment on the treated (ATT) and the average treatment effect on untreated (ATU) estimators, which estimate the impact of organic fertilizer on households who did adopt and the potential impact on those who did not, are applied respectively. A manuscript based on this chapter has been revised and re-submitted to the *Journal of Agricultural and Applied Economics*.

Chapter 5 applies the generalized multinomial logit (G-MNL) model to estimate rural farmers' willingness to pay for a hypothetical MSW compost and its attributes. The analysis allowed potential sources of preference and scale-heterogeneity across farmers to be identified and quantified. Finally, chapter 6 presents conclusions and draws policy implications.

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Chapter 2

Organic Fertilizer Use by Smallholder Farmers: Typology of Management Approaches in Northern Ghana

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Abstract

An understanding of the nexus of organic fertilizer use decisions that smallholder farmers take is essential to designing relevant policy to support adoption in Sub-Saharan Africa. In this paper, we applied Exploratory Factor Analysis (EFA) on observed farmer decisions to identify a set of common management approaches that farmers in the northeastern part of Ghana adopt in using organic fertilizer. After identification, Seemingly Unrelated Regression (SUR) analysis was applied to relate each approach to farmer characteristics that influence uptake decisions. The EFA identified four approaches: Augmentary Compost Use Approach, Urban Human Waste Organic Fertilizer Approach, Integrated Livestock Manure Approach, and Mineral Fertilizer Cost Constraint Organic Approach. Each of the first three approaches involves a set of strategic farmer decisions which could be supported to increase organic fertilizer use. The SUR analysis showed that uptake of each approach is affected by a different subset of farmer characteristics. However, participation in organic fertilizer training positively influences the adoption of all the approaches. Thus, we recommend free training of smallholder farmers as a core element of any policy package to support organic fertilizer adoption.

Keywords: organic fertilizer, farmers' decisions, management approaches, soil nutrients, northeastern Ghana

2.1 Introduction

Three main factors drive the need to promote organic soil nutrient management among smallholder farmers in Sub-Saharan Africa (SSA): (1) excessive nutrient mining and related soil change factors, including erosion, loss of soil organic matter and biodiversity (Tittonell and Giller, 2013 and Atakora *et al.*, 2014), (2) lack of access to sufficient quantities of mineral fertilizers, and (3) the quest to develop organic fertilizer markets as cost-effective systems of urban waste disposal.

Due to decades of soil nutrient mining through continuous crop removal, Africa's soil is the poorest worldwide (Tittonell and Giller, 2013). AfDB (2006) estimates that the continent loses over US\$4 billion worth of soil nutrients each year, thus eroding its ability to produce enough food to feed itself. Depletion of soil nutrients through crop removal (i.e., NPK >60kg/ha/season, according to Gregory and Bumb, 2006), and other factors like leaching and erosion have degraded agricultural lands in the savannah areas of SSA (Tittonell and Giller, 2013). Furthermore, the subsistence farming population is also rapidly growing in the region (FAO, 2015), while arable land available to farm households continues to decline (Awoonor, 2012 and Bellwood-Howard, 2013). This situation compels farmers to practice continuous and intensive cropping regimes instead of fallowing lands to restore soil health (Bellwood-Howard, 2013; Atakora *et al.*, 2014; Danquah *et al.*, 2019 and Owusu *et al.*, 2020). Yield, which is about a sixth of the output of advanced agriculture (AfDB, 2006) is still on a downward trend for many staple crops (Tittonell and Giller, 2013). Thus, adoption and increased application of mineral fertilizers are critical for farmers in the region to sustain output levels and food security. Mineral fertilizers contain high amounts of macro and micro-nutrients lacking in most African soils in a readily accessible manner to crops (Tittonell and Giller, 2013 and Sudradjat *et al.*, 2018).

However, SSA countries face many challenges in accessing mineral fertilizers amid poorly developed markets (Tittonell and Giller, 2013; and Sheahan and Barrett, 2017). Due to high freight and distribution costs, nearly all mineral fertilizers are expensive imports in the region. Thus, increasing fertilizer import under current national fertilizer subsidy programs raises public sector expenditure and consequently piles foreign exchange deficits (Gregory and Bumb 2006). Despite government subsidies, the cost of mineral fertilizer is relatively high for the average farm household to acquire without compromising some consumption needs (Zingori *et al.*, 2011). Also,

physical access limitations in remote areas often impede timely procurement and efficient utilization of the input to ensure increased returns (Thelma *et al.*, 2017).

Even though conventional literature suggests a very low use of mineral fertilizer in SSA, recent evidence shows that farmers in northern Ghana, for instance, are increasingly reliant on mineral fertilizers (Sheahan and Barrett, 2017). The quantities of fertilizer applied in staple grain fields, in particular, seem economically sufficient (Liverpool-Tasie *et al.*, 2017). The next most crucial aspect of mineral fertilizer usage to consider is balancing the benefits of increased application with negative environmental consequences that may arise. Generally, continuous but unregulated use of mineral fertilizer negatively affects soil health by hampering important soil microbial functions (Prashar and Shah, 2016). Scientific evidence (e.g., Atakora *et al.*, 2014) points to acidity and damaged soil structure, where farmers have repeatedly applied the same formulation of mineral fertilizers for years without balancing with organic matter. Such soils have become so impoverished that experts fear they no longer respond to fertilizer increase; hence, farmers do not get the expected benefits from high-value input investments (Tittonell and Giller, 2013 and Atakora *et al.*, 2014).

Meanwhile, organic fertilizers play a significant role in reducing the risks associated with mineral fertilizer use. Organic fertilizers provide natural carbon essential for improving and sustaining the soil's physical, chemical, and biological properties under continuous and intensive cultivation (Sudradjat *et al.*, 2018). Besides, increasing organic fertilizer use presents opportunities to manage public waste and GHG emissions through controlled decomposition. Hence, experts recommend that farmlands be used as carbon sinks for the biodegradable fraction of urban waste (Galgani *et al.*, 2014; UNFCCC, 2015; and the Republic of Ghana, 2015).

However, adopting organic fertilizer use is also not without setbacks. The input is currently not on the market for farmers to buy. Farmers have to generate/source raw material and produce it by themselves or make arrangements with sources where some readily useable forms exist (Tittonell and Giller, 2013). Yet, such types of organic fertilizer generally contain low levels of essential soil nutrients (NPK), are slow in releasing the nutrients, and to the extent that organic matter sources are limiting, farmers are unable to secure sufficient quantities to meet their needs (Harris, 2001 and Tittonell and Giller, 2013). These challenges further stress the need to combine organic with mineral fertilizers, not only as complements but also as supplements.

For these reasons, farmers, particularly in northeastern Ghana, are being encouraged by the government and other agricultural agencies (e.g., Presbyterian Agricultural Stations - PAS) to

apply organic in combination with mineral fertilizers. These agencies have so far been supporting smallholder farmers to prepare and use compost to fertilize cereal fields. However, smallholder farmers are heterogeneous regarding traditional organic soil practices (Pandey, 2010). A lack of alternatives to cater for different preferences and resource settings is a major limitation to the technology's uptake (Tittonell *et al.*, 2005; Zingori *et al.*, 2007; and Giller *et al.*, 2011). Hence, promoting only compost use among farmers will not achieve the desired rate of organic fertilizer use in the area.

An attractive organic fertilizer policy should have options compatible with and exploit pre-existing organic fertilizer use knowledge, motives, practices, skills, and other legacy resources of target farmers (Quansah *et al.*, 2001). Designing such a policy requires that policymakers consider essential differences of existing organic fertilizer practices among target farmers. However, such information is currently lacking. The literature on organic fertilizer adoption is silent about how smallholder farmers take pragmatic decisions/actions to secure and use the input. Though policy planners often gather such information through participatory appraisals involving farmers, prior to policy design, recent scientific evidence (i.e., Henning *et al.*, 2019) revealed that donor and research interests rather than those of farmers drive donor project design in developing countries. Thus, empirically objective information regarding how smallholder farmers decide to use organic soil amendments remains unavailable.

As a contribution towards filling this gap, this paper operationalized Mowo *et al.*'s (2006) farmer decision-framework and collected observational data on farmer practices to identify typologies of organic fertilizer decisions/practices. First, an explanatory factor analysis (EFA) was performed on a data set of organic fertilizer use decisions. Four typologies, hereafter called organic fertilizer management (OFM) approaches, were identified. The approaches were characterized by farmers' socioeconomic/plot characteristics in a further analysis using a seemingly unrelated regression (SUR) system of equations.

This study extends the organic fertilizer adoption literature by providing empirical descriptions of management approaches that smallholder farmers adopt to use organic fertilizer. To the extent that policy planning requires information on background practices under specific farming conditions, this study's results have significant implications for organic fertilizer policy design in SSA and Ghana, in particular.

2.2 Organic Soil Amendment in Northern Ghana

Two strands of previous studies on organic fertilizer use in Ghana exist in the literature. The first

is a set of studies focusing on the feasibility of using certain kinds of biomass like urban biodegradable waste or refuse and sewage materials as fertilizers (e.g., Cofie *et al.*, 2005 and Nimoh *et al.*, 2014). The second strand, which is more relevant to this study, includes studies that examine farmers' organic soil maintenance practices, particularly in the northern part of the country (e.g., Quansah *et al.*, 2001).

Evidence from the latter strand suggests that smallholder farmers in northern Ghana are historically aware of the declining trend in soil fertility, causes, and its impact on crop yields (Dittoh, 1999; and Bellwood-Howard, 2013). Many farmers, therefore, adopted some traditional ways to manage their soils judiciously. When there was plenty of unused arable land in the area, natural nutrients recycling, such as fallowing by shifting cultivation, was used to improve farmland soil conditions (Quansah *et al.*, 2001). For fields around farmers' homes, biomass transfer strategies such as composting and application of manure found in the vicinity were used to sustain soil nutrient levels (Quansah *et al.*, 2001; and Saïdou *et al.*, 2004). Because of the increasing scarcity of arable land and the need to intensify cultivation, natural nutrient recycling processes are no longer feasible nowadays. Farmers now rely on external sources of nutrients, either near their homes or further afield (Saïdou *et al.*, 2004). Although majority of the farmers now use mineral fertilizer as the primary external nutrient source, they combine the mineral with organic soil amendments.

When Quansah *et al.* (2001) surveyed farmers' perceptions on soil organic matter and reviewed studies on traditional methods of organic soil management, many of the strategies (e.g., shifting cultivation, land rotation, and slash-and-plant) they found in northern Ghana were internal processes of soil nutrient recycling, including fallowing. Fallowing land to restore soil fertility is no longer feasible because the growing farmer-population in the area has increased demand and, thus, the scarcity of arable land. Concerning the use of organic fertilizers as external inputs, they observed the primary materials farmers use and discussed constraints related to using such materials. They, however, noted that farmer-support agencies were promoting modern organic technologies (e.g., green manuring and agroforestry) even though farmers rarely practiced them. As Saïdou *et al.* (2004) and Dionys *et al.* (2013) indicated for similar settings, farmers in northeastern Ghana anecdotally adapt to declining crop yields due to poor soils by modernizing their traditional soil amendment practices to maintain productivity. However, their effort is limited because of a lack of organic materials exacerbated by their competing use for fuel and construction. Hence, there is a need to build farmers' capacity to scale-up the input use (Government of Ghana, 2015). In support of farmers towards this end, the government and other

agricultural agencies (e.g., the Presbyterian Agriculture Station - PAS) have been sensitizing and building farmers' capacity to source, process, and use biodegradable materials as organic fertilizer. However, so far, these efforts have focused on compost preparation and efficient methods application on field, while evidence from previous studies suggests that several other options could be developed (Cofie *et al.*, 2005; Cofie *et al.*, 2010 and Nimoh *et al.*, 2014).

2.3 Methodology

2.3.1 Common tools for typological studies

Studies of farming systems, which addressed objectives similar to those of the present study, have used typological analysis to classify prevailing practices among farmers and identified farmer characteristics that determine their tendency to engage in those sets of practices (e.g., Vanclay, 2005 and Chikowo *et al.*, 2014). Such analyses usually employ multivariate statistical approaches using a variety of techniques (Richarme, 2002). The most commonly applied techniques in this regard include factor analysis (FA), principal component analysis (PCA) and cluster analysis (CA) (McBride and Johnson 2006; Todde *et al.*, 2016 and Kamau *et al.*, 2018).

The usefulness of each of these techniques is situation-dependent. Suppose the analyst believes that certain underlying constructs influence the covariations among the variables (observed decisions), but there is no prior information on the number of constructs. In that case, exploratory factor analysis (EFA) is an appropriate technique to identify the constructs. EFA segregates the variables into parsimonious groups of few inter-correlated ones, influenced by the supposed latent constructs called factors. On the other hand, if there is prior evidence of the number and nature of factors expected to emerge from the analysis, confirmatory factor analysis (CFA) should be applied (Fabrigar *et al.*, 1999, and O' Rourke and Hatcher, 2013).

The classification techniques above have generally used a wide range of variables, including farm enterprise structural, physical, managerial, and financial performance data, to identify typologies. The typologies are further characterized using household characteristics, resource endowment, institutional/social-capital and farm characteristic variables (see Jha *et al.*, 2000; McBride and Johnson 2006 and Pandey, 2010). We defined organic fertilizer management, descriptively, as a set of related decisions/actions that a farmer takes at the household level to obtain the input for use (Dillon, 1997). From the literature, followed by farmers' validation, we identified a universal set of observable organic fertilizer use decisions (see Lagerkvist *et al.*, 2015) to support possible sub-sets of farmers' decisions in the study area. Since there is no prior information about how farmers take organic fertilizer use decisions, we could not assume any number or nature of

expected factors. Hence, we applied EFA on farmers' observed decisions/actions to identify common factors as OFM approaches.

2.3.2 *Conceptual framework*

Since the 1960s, farms in developing countries are noted to be complex sets of inter-related components, including crop and livestock enterprises, as well as farm management. These components function together as a purposeful and open stochastic dynamic system, with the various components functioning as subsystems. One cannot deduce the total value of the system's function by considering components in isolation (i.e., using the reductionist approach) (McConnell and Dillon, 1997). Besides the complexity of the systems, such farms are also managed implicitly: farmers do not formalize what they do by keeping records or institute operational systems. However, they are able to provide self-reported information on management decisions and practices during formal farm surveys (Norman *et al.*, 1995). Therefore, farm management studies seeking to understand how farmers manage such systems or any of their components could adopt a systems approach to analyzing reported farm-level data.

This study examined organic fertilizer management approaches within a broader context of sustainable soil management under conditions where farmers cannot buy the input from the market and instead must generate it from a farm input subsystem. The subsystem is a backwardly integrated enterprise that must be managed to produce organic fertilizer for use in cereal enterprise (McConnell and Dillon, 1997).

To identify the approaches farmers adopt to manage the input production subsystem, we assumed they manage it implicitly according to Mowo *et al.*'s (2006) soil fertility decision-framework (see Figure 2.1) within which smallholder farmers operate. Under this framework, the farmer plays a triple role: entrepreneurial, managerial, and craftsmanship (laborer). As an entrepreneur, he or she defines his/her organic fertilizer use goals and devises strategies to meet the goals. The farmer allocates resources, as a manager, towards implementing the plan to achieve the goals. Systematically, he or she also manages the input generation process following the 5-stage soil management decision-cycle shown in Figure 2.1. A farmer implicitly analyses his/her organic soil fertility needs and thereby decides on specific objectives for using organic fertilizer. He/she then chooses from available alternatives the type of organic fertilizer to use and therefore selects materials needed to process it.

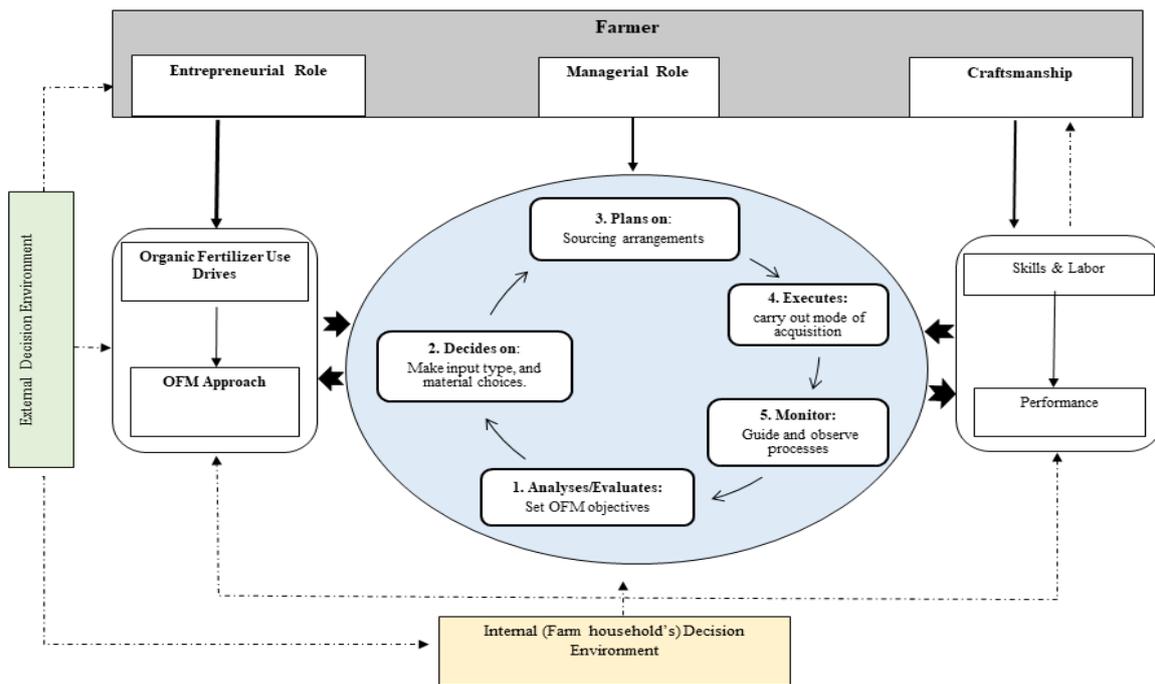


Figure 2.1: Smallholder farmers' decision framework for managing soil nutrients
 Source: Modified after Mowo *et al.* (2006).

These decisions feed into plans to source the materials. The farmer executes the plans by procuring the input or its raw materials and processing them. As a craftsman, the farmer employs skills (own or hired) to carry out and monitor activities required to obtain the input for a given cropping season (Mowo *et al.*, 2006). The process and its performance are implicitly evaluated to inform the need for changes in the strategy at the end of each season. Each stage of the operations management-cycle shown in Figure 1 involves several alternative decisions/actions from which a farmer can choose.

Farmers' goals influence their organic fertilizer use strategies (Norman *et al.*, 1995), which, in turn, influence the decisions/actions taken within the management cycle. A set of decisions/actions taken at the various stages of the cycle forms a trajectory of management, depicting a latent construct underlying farmer's decisions. Different constructs that influence various trajectories of observed organic fertilizer use decisions, in our case, are the equivalence of Mowo *et al.*'s (2006) strategies that farmers employ to meet their organic fertilizer use goals. We shall subsequently refer to these strategies as organic fertilizer management (OFM) approaches.

The preceding discussion implies that the OFM approach adopted by a farmer is a construct and cannot be observed by the researcher. The analyst, however, does observe a set of decisions/actions that a farmer took. This set of decisions/actions is a manifestation of the

underlying approach and therefore identifies a farmers' OFM approach (McBride and Johnson, 2006). However, it is practically not possible and even needless to identify an individual approach of farmers. Instead, groups of farmers may take the same trajectory of decisions/actions, for that matter, one OFM approach. This implies that observation of a wide range of farmer-decision sets from a population of farmers manifests existing OFM approaches adopted by farmers. One can identify the approaches through a typological analysis of the observed management decisions/actions (see Table 2.1) (McBride and Johnson, 2006; Chikowo *et al.*, 2014; Todde *et al.*, 2016).

It is well established in the literature (e.g., Mowo *et al.*, 2006; Shiferaw *et al.*, 2009; Kamanga *et al.*, 2009; and Mulwa *et al.*, 2017) that farmers' background factors influence their OFM decisions. These factors include *inter alia* human capital status, physical resource endowment characteristics, farming environment (soil and biodiversity), and the external environment (institutional and social capital, political, technological, and economic context). These factors shape their farm objectives, perceptions about cost/benefits associated with various OFM decisions, and set constraints within which the decisions are made.

Assuming that a farmer chooses to adopt an OFM approach that maximizes expected benefit from organic fertilizer use under constraints set by his/her background factors, a function that characterizes the relationship between the adopted approach and farmer's background factors can be derived to explain the uptake of the latent approaches (Abdulai and Huffman, 2014; Abdulai 2016; Tambo and Wüncher, 2017; and Danquah *et al.*, 2019). Following McBride and Johnson (2006), we assumed that the latent OFM approaches are characterized by a set of observed farmer characteristics and farming context variables (see Table 2.2).

2.3.3 *Data and description of variables*

This study used an observational data set of the 2017/18 crop season, obtained from a multistage random sample of 250 smallholder cereal farmers in northeastern Ghana. The farmers provided the data in response to a set of structured questions during computer-assisted personal interviews (CAPI) with enumerators. The questionnaire solicited two main categories of variables. The first category is the list of organic fertilizer decision variables in Table 2.1 (referred to as decisions/actions).

Table 2.1: OFM decision/practice variables used in EFA to identify OFM approaches

Binary Decision Variable	Description and Measurement of Variable	% Sample
Organic fertilizer use objectives/motivations		
Compl-Mineral	Apply organic fertilizer to help the soil for mineral fertilizer to work well	59
Cost-Reduction	Apply organic fertilizer because it is cheaper than mineral fertilization.	61
Organic-Standards*	Apply only organic fertilizer because I produce for an organic market.	0
Affordability	Apply organic fertilizer because I cannot afford mineral fertilizer.	16
Water-Conservation	Apply organic fertilizer because it helps crops to resist drought.	59
Profit	It is more profitable to employ organic fertilizer than mineral fertilization.	71
Suppl-Mineral	Apply organic fertilizer because I am not able to apply enough mineral fertilizer.	72
Type of organic fertilizer used		
Any/Mixed	Apply any type of organic fertilizer available to me.	63
Compost	Apply compost on farm.	56
Manure	Use only farmyard manure as organic fertilizer.	20
Slurry/Sewage	Use toilet/urban waste products on farm.	22
The main component of fertilizer		
Animal-Droppings	The primary material of organic fertilizer is livestock/poultry droppings.	20
Domestic-Refuse	The primary material of organic matter is household refuse damp black soil.	33
Crop-Residue*	The primary material of the organic fertilizer used is crop residue.	96
Human-Excreta	The main component of organic fertilizer is human waste/excreta.	14
Mode of acquisition		
Free-Collection	Secure organic fertilizer/ materials from a free source in the community.	28
Own-Production	Gather materials and prepare compost in a pit at home/on the farm.	59
Exchange	Obtain organic fertilizer from a non-commercial source (payment in kind).	44
Purchase	Buy organic fertilizer from a commercial source.	10
Sourcing Plan		
Waste-Gathering	Built a pit for decomposing animal and household waste into natural manure.	46
Keep-Livestock	Keep livestock/poultry so that I can get manure to apply on crops.	41
Contract-Herdsman	Contracted herdsman/poultry farmers to supply manure.	50
No-Arrangement	Collect organic fertilizer from any locally available source when needed.	40
Arrange-Residue	Arrange for crop residues/by-products from other places for use.	38
Arrange-Excreta	Arrange with waste disposers for slurry/ sewage matter.	12

(*)These are variables with almost constant values observed among the surveyed farmers. Thus, they were not included in the analysis.

Many of these decisions have been promoted in the study area by policy agents like NREGP, AGRA, and PAS (Martey, 2018). Based on a literature review (e.g., Lagervist *et al.*, 2015), the questionnaire captured 35 organic fertilizer decisions, but only 25 of these decisions were observed during the face-to-face CAPI with sampled farmers. These are grouped under the five phases (stages) of the decision-cycle in Figure 1

Variables include organic fertilizer use objectives at phase 1, organic fertilizer types chosen at phase 2, and the main material component used, also at phase 2. Other decision variables indicate the sourcing plan/arrangement(s) a farmer adopts at phase 3 and the alternative model(s) of acquisition used at phase 4. Decisions taken at the monitoring stage (phase 5) have no observable outcomes; hence they are not empirically represented by any observed variable. They, however, directly affect phase 1 decision outcomes.

The second category of variables solicited by the study questionnaire includes farmer background factors, which we shall subsequently refer to as farmer/plot characteristics. These are classified further under four latent background variables. The first is household characteristics, which include gender, age and education of the farmer, household size, family labor force, and production purpose. Other household characteristics are participation in organic soil management (training), farmer's risk attitude, and diversity of crops on the farm (CDI) (Mulwa *et al.*, 2017). We specify these variables to capture the effect of human capital on farmers' tendency to adopt the various OFM approaches (Shiferaw *et al.*, 2009). The second class of background variables comprises the total value of farm assets, non-farm income work, livestock size, and plot size measured in hectares. These together represent a farmer's physical resource endowment.

The third class of variables captures social capital and information access. These include whether a farmer has benefited from some soil fertility management policy, whether a farmer belongs to a farmer-based organization and whether he/she has contact with extension services. Finally, we also included farm-specific and geographical location variables, which include the cost of mineral fertilizer used per hectare, the distance (walking minutes) to cereal plot from a farmer's home, tenure of farmland, mean score of soil-quality and geographical location (zone) of a farmer/farm. Table 2.2 provides the list, description and summary statistics of all farmer/plot variables used in this study.

We used the observed OFM decision data for EFA to identify common OFM approaches while using the farmer/plot characteristic variables as independent variables in the second-step characterization regressions to identify farmer characteristics that explain the uptake of each of the OFM approaches. We used post-EFA factor scores of farmers to represent the OFM approaches as dependent variables in the characterization regressions. In the next section, we present the empirical models and procedure for the two-step multivariate analysis (i.e., EFA and the characterization regressions)

Table 2.2: Farmer/plot variables used in SUR characterization model

Variable	Description/measurement	Mean \pm
Independent variables		
Household Characteristics		
Gender	Sex of farmer (Dummy)	0.87 \pm NA
Age	Age (Number of years)	42 \pm 13
Education	Education (number of years of school)	5 \pm 6
Household size	Household size (Number of people)	10 \pm 4
Household Labor force	Family labor force (Number of adult persons who work on the farm)	6 \pm 3
Production purpose	Dummy (Subsistence=0, commercial=1)	0
Training	Dummy (untrained =0, trained=1)	0.4 \pm 0.5
Risk attitude ²	Farmer's willingness to take a risk (Score 0-10)	6.9 \pm 3
Crop diversification ³	Crop enterprise diversity in the household (CDI) index	0.6 \pm 0.2
Physical resource endowment		
Household income	The total annual income (in Ghana Cedis) of working members	4242 \pm 798
Farm assets	Value of farm assets: plows, carts and drought animals(in Ghana Cedis)	8504 \pm 1724
Non-farm income	Household has non-farm income source (no=0, yes=1)	0.2 \pm NA
Livestock size	Number of tropical livestock units	5.58 \pm 10.3
Plot size	Number of hectares	0.5 \pm 0.8
Institutional/social capital		
Beneficiary	A beneficiary of organic soil fertility intervention (no= 0, yes=1)	0.3 \pm NA
Fbo membership	Farmer belongs to farm-based organization (no= 0, yes=1)	0.3 \pm NA
Extension contact	Has contact with extension service (no=0, yes=1)	0.3 \pm NA
Plot characteristics		
Locations:	Categorical : 0. Bunkpurugu, 1. Langbinsi, 2. Garu West, 3. Garu East	N/A
Min-fertilizer expend.	Mineral fertilizer cost per hectare (Ghana Cedis)	567 \pm 552.
Distance to farm	The distance of plot from farmer's home (Minutes of walk)	22.8 \pm 26.8
Land tenure	category (Owned=0 rented=1)	0.1 \pm NA
Soil Quality rate	Mean of soil-qualities scores. Range (Poor =1 to Good =3)	2.15 \pm 0.39
Dependent variables for SUR equations characterizing		
Fact-Score1	Farmer's score on factor one (number)	7 \pm 0.93
Fact-Score2	Farmer's score on factor two (number)	7 \pm 0.93
Fact-Score3	Farmer's score on factor three (number)	7 \pm 0.92
Fact-Score4	Farmer's score on factor four (number)	7 \pm 0.93

Factor scores of farmers on approaches were obtained by Stata's post factor analysis command "Score."

2.3.4 Empirical EFA model and procedure

Assuming that some underlying but unknown number of constructs (latent factors) influence patterns of decisions and actions farmers take to secure organic fertilizer for their plots,

²As in Xiaohao *et al.* (2010) and Dohmen *et al.* (2011), risk willingness scores were obtained by asking farmers to grade themselves on an eleven-point scale of their readiness to take a risk in general. To validate the scores, farmers were presented with a hypothetical lottery case to make choices, during which they could attempt to play more than once. Options with higher levels of pay-off are associated with fewer numbers of trials possible. Choosing an option with more rounds of trials implies the avoidance of risky situations.

³We estimated crop diversification as an index by subtracting the Herfindahl index (HI) from one (1-HI), where HI was calculated as follows: $HI = \sum_{i=1}^n s_i^2$, where s_i is the proportion of *i*th crop, given as $s_i = \frac{A_i}{\sum_{i=1}^n A_i}$ and, A_i = Area under *i*th crop, $\sum_{i=1}^n A_i$ = Total cropped area, and $i = 1, 2, 3, 4, \dots, n$ number of crops considered. In this study we used eight crops common in the study areas to calculate the index. The ranges from 0 (specialization) to 1 (complete diversification). Any value above zero signifies diversification. Precisely, we estimated the index.

Explanatory Factor Analysis (EFA) can be applied to the data set of observed farmer decisions to identify the latent factors, here referred to as OFM approaches. (O' Rourke and Hatcher, 2013). The EFA model expresses each OFM decision variable as a linear combination of the underlying OFM approaches to be identified. With J decision variables, J multivariate regressions on an unknown set of management approaches as covariates are specified as (O'Rourke and Hatcher, 2013);

$$\left\{ \begin{array}{l} V_1 = \beta_{11}F_1 + \beta_{21}F_2 + \dots + \beta_{k1}F_k + \mu_1 \\ \cdot \\ \cdot \\ \cdot \\ V_j = \beta_{1j}F_1 + \beta_{2j}F_2 + \dots + \beta_{kj}F_k + \mu_j \end{array} \right\}, \quad (1)$$

where V is an observed OFM decision variable with $j=1, \dots, J$, and $F=1, \dots, k$ are the latent factors (underlying OFM approaches) influencing the variables $V=1, \dots, j$, β is a matrix of linear coefficients, known as estimated factor loading of factors $1, \dots, k$ on $V=1, \dots, j$, and $\mu=1, \dots, j$ is a vector of residuals known as unique factors, analogous to regression error terms (Timm, 2002; McBride and Johnson, 2006; and O' Rourke and Hatcher, 2013).

If the data is normally distributed, the factors are best extracted (i.e., the system of equations is estimated) by maximum likelihood. However, we could not assume a multivariate normal distribution of the data because all variables included in the analysis are binary. We thus applied Principal Axis Factoring (PAF) to extract the factors – a method that does not require normally distributed data. The number of factors obtained from the initial extraction equals the number of OFM approaches. However, only a few of these could be meaningfully interpreted and met other criteria for inclusion in the final extraction (McBride and Johnson, 2006; O'Rourke and Hatcher, 2013 and Osborne, 2015). We applied the four criteria in selecting the factors recommended by Beavers *et al.* (2013) and O'Rourke and Hatcher (2013): (1) Kaiser's (eigenvalue ≥ 1) rule, (2) the graphical scree-test, (3) the proportion of total variance explained by a factor and (4) the interpretability (meaningfulness) of factor rules.

The first four of the initial factors met at least three of the criteria and were retained. As recommended for analyses involving human behavior (Osborne, 2015), we expected that some form of correlation exists between potential OFM approaches (the factors). Hence, we rotated the factors by the **oblique promax algorithm**, which captures such potential correlation, to arrive at a simple structure. The simple structure, in this case, had each factor loading significantly on only several (3-5) decision/action variables. Following McBride and Johnson (2006) and O'Rourke and Hatcher (2013), we considered factor loadings of ≥ 0.4 significant for interpreting the results, even though a factor loading of 0.3, under the ideal condition that a factor explains about 50% of the

variance in variables has been suggested (Beavers *et al.*, 2013). We labeled each factor (OFM approach) by the description of the OFM decision on which the factor loaded most significantly and described it using all decisions on which the factor loaded.

2.3.5 Characterization using seemingly unrelated regression (SUR) analysis

After EFA identified the OFM approaches, the next objective was to characterize the approaches by farmer/plot characteristics that explain their adoption. Assuming farmers' tendency to adopt a given OFM approach is driven by their background variables (Table 2), we expressed each OFM approach as a function of observed farmer/plot variables to identify characteristics that empirically affect adoption. In this case, the OFM approaches, as dependent variables, are not observed but can be represented by their factor scores. Therefore, we evaluated each farmer's score on each of the four factors (OFM approaches) following the EFA. These are used as dependent variables, representing the approaches in the characterization regression model.

However, we had to be sure that indeterminacy in the factor-score variables is low enough to estimate empirically reliable characterization equations for the OFM approaches. We thus assessed the degree of factor score determinacy by calculating squared correlation coefficients (ρ^2) of factor score estimates of split samples (Green, 1976) obtained by regression method and by Bartlett's (1937) method. In each case, the ρ^2 obtained was higher than 0.75, indicating that factor score indeterminacy is low (<0.25). Since the Bartlett factor score estimates are most likely the true factor scores (DiStefano *et al.*, 2009) and produce unbiased regression parameters (Devlieger *et al.*, 2015), we used them as the dependent variables for the characterization analysis. Furthermore, since factor-score estimates are equivalent to z-scores, they should be regressed on z-score standardized values of the independent variables; otherwise, the resultant model estimates cannot be interpreted (Zuccaro, 2007). Accordingly, we z-standardized the socio-economic variables in Table 2 before using them as regressors. The characterization model involves K approaches, each to be regressed on (i.e., characterized by) the same set of $x = 1, 2, \dots, m$ farmer/plot characteristic variables of $N = i, \dots, n$ observations, forming $K = 1, \dots, k$ simultaneous equation system;

$$\left\{ \begin{array}{l} S_{1i} = \alpha_{11}x_{1i} + \alpha_{21}x_{2i} + \dots + \alpha_{m1}x_{mi} + \varepsilon_{1i} \\ \cdot \quad \cdot \quad \cdot \quad \cdot \quad \dots \quad \cdot \quad \cdot \quad \cdot \\ \cdot \quad \cdot \quad \cdot \quad \cdot \quad \dots \quad \cdot \quad \cdot \quad \cdot \\ S_{ki} = \alpha_{1k}x_{1k} + \alpha_{2k}x_{2k} + \dots + \alpha_{mk}x_{mk} + \varepsilon_k \end{array} \right\}, K= 1, 2, \dots, k; x= 1, 2, \dots, m; i=1, 2, \dots, N \quad (2)$$

where S_{ki} is farmer i^{th} score on factor (OFM approach) k , which is to be explained by the k^{th} equation, ε_{ki} is a random error term associated with the i^{th} farmer in the k^{th} equation, while α_1 to α_m

is a vector of coefficients (effects) of farm/farmer characteristics on farmers' tendency to adopt the k^{th} OFM approach.

Equation system (2) shows that for every i^{th} farmer (observation), there are ε_{1i} to ε_{ki} random errors (i.e., one for each k^{th} equation) to be estimated. Each of these equations can be efficiently and consistently estimated by ordinary least squares (OLS) (e.g., Jha *et al.*, 2000 and Pandey, 2010) in a situation where the factor scores (i.e., S_{ks}) are obtained from orthogonal factors (Osborne, 2015) such that they are uncorrelated, having a mean of $E[\varepsilon_k|x_1, \dots, x_m] = 0$ and a variance $E[\varepsilon_k \varepsilon_k' | x_1, \dots, x_m] = \sigma_{kk} I_N$. These conditions imply normal distribution and homoscedasticity of error terms. For oblique factors, as in this case, however, some of the factors (OFM approaches) may not be entirely distinct, i.e., correlated with each other (Gorsuch, 1983). Once factor scores are correlated, the error terms associated with farmer i across equations will also correlate with each other. Therefore, the use of oblique factor scores as dependent variables of equation system (2) implies correlated cross-equation ε_{ks} of observations. Hence, estimation by OLS will give consistent but not efficient αs (Greene, 2018). To obtain consistent and efficient estimates of αs , an econometric setup that captures and isolates the error correlation terms must be employed. We adopted the Seemingly Unrelated Regressions (SUR) framework, which, by means of the generalized least squares (GLS) estimation, isolates between-equation error correlation coefficients to obtain efficient parameters. In the SUR setup, we stacked the observations data sets and obtained a compactly specified model as (Rao *et al.*, 2008 and Greene, 2018):

$$\begin{bmatrix} S_1 \\ \vdots \\ S_k \end{bmatrix} = \begin{bmatrix} \mathbf{X}_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \mathbf{X}_K \end{bmatrix} \begin{pmatrix} \alpha_1 \\ \vdots \\ \alpha_K \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_K \end{pmatrix} = \mathbf{X}\alpha + \varepsilon, \quad (3)$$

where \mathbf{X}_k is a matrix of observed farmer characteristics, α_k is a vector of coefficients associated with equation k to be estimated, $\varepsilon = [\varepsilon_1', \dots, \varepsilon_K']'$ is a $KN \times 1$ vector of measurement errors with conditional expectation, $E[\varepsilon | \mathbf{X}_1, \dots, \mathbf{X}_K] = 0$. The errors are uncorrelated across observations but are correlated across equations, such that $E[\varepsilon_{ki} \varepsilon_{kn} | \mathbf{X}_1, \dots, \mathbf{X}_K] = \sigma_{in}$, if $i = n$, and 0 if $i \neq n$. The entire model error matrix is given as (Rao *et al.*, 2008 and Greene, 2018):

$$E[\varepsilon \varepsilon' | \mathbf{X}_1, \dots, \mathbf{X}_K] = \sigma_{in} I_N = \begin{bmatrix} \sigma_{11} \mathbf{I} & \dots & \sigma_{1K} \mathbf{I} \\ \vdots & \dots & \vdots \\ \sigma_{K1} \mathbf{I} & \dots & \sigma_{KK} \mathbf{I} \end{bmatrix} = \Sigma \otimes \mathbf{I}, \quad (4)$$

where $\Sigma = \begin{bmatrix} \sigma_{11} & \dots & \sigma_{1K} \\ \vdots & \dots & \vdots \\ \sigma_{K1} & \dots & \sigma_{KK} \end{bmatrix}$ is an $M \times M$ error covariance matrix for the i^{th} observation, \otimes is the

Kronecker product operator and \mathbf{I} is a $K \times K$ identity matrix.

After estimation, if empirical σ_{in} equals zero for $i \neq n$, then the equations are truly unrelated, and there is no efficiency gain in α_k by the use of a GLS estimator over OLS. On the other hand, if for any pair of the equations (i.e., OFM approaches), σ_{in} is significantly different from zero, the approaches are related through some common OFM decisions/actions. Previous studies (e.g., McBride and Johnson, 2006) have used the SUR framework in similar circumstances, but only for testing differences in coefficients of paired regressions. Even though we found very weak correlations between the factors, since we assumed correlated factors (OFM approaches) in EFA, we applied the SUR estimator mainly to obtain efficient estimates by correcting any bias arising from such correlations.

2.4 Results and Discussion

2.4.1 Identification of OFM approaches

We extracted initial factors by Principal Axis Factoring after ascertaining that all variables had Cronbach alpha ≥ 0.85 , the test of sphericity was significant at 1%, and Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy is about 0.83. An assessment of the results in Table 2.3, using the eigenvalue \geq one (mineigen) criterion and scree test result supported by interpretability, revealed that four latent factors together explain the variation in organic fertilizer decisions/actions data. The first factor accounted for about 37% of the total variance, the second for about 29%, the third for roughly 17%, and the fourth for approximately 8%. Together, they explained about 92% of the total variance in the data. Although it explains up to 5% of the total variance, the fifth factor had an eigenvalue less than 1, with only two significant loadings with no meaningful interpretation.

Table 2.3: Eigenvalues of initial factors

Initial factor	Eigenvalue	Proportion of variance explained	Cumulative variance explained
Factor 1	4.90223	0.3725	0.3725
Factor 2	3.87251	0.2943	0.6668
Factor 3	2.24467	0.1706	0.8373
Factor 4	1.06372	0.0808	0.9182
Factor 5	0.70240	0.0534	0.9715
Factor 6	0.55379	0.0421	1.0136
Factor 7	0.43278	0.0329	1.0465
Factor 8	0.27122	0.0206	1.0671
Factor 9	0.24188	0.0184	1.0855
Factor 10	0.16774	0.0127	1.0982
Factor 11	0.06019	0.0046	1.1028
Factor 12	0.04237	0.0032	1.1060
Factor 13	-0.01239	-0.0009	1.1051
Factor 14	-0.04402	-0.0033	1.1017
Factor 15	-0.05965	-0.0045	1.0972
Factor 16	-0.08428	-0.0064	1.0908
Factor 17	-0.11809	-0.0090	1.0818
Factor 18	-0.12568	-0.0095	1.0723
Factor 19	-0.15103	-0.0115	1.0608
Factor 20	-0.15452	-0.0117	1.0491
Factor 21	-0.19352	-0.0147	1.0344
Factor 22	-0.20583	-0.0156	1.0187
Factor 23	-0.24634	-0.0187	1.0000

LR test: independent vs. saturated: (253) = 2605.52 Prob > = 0.000

Bold factors & values are the retained factors and their indexes, respectively.

The results in Table 2.4 are the rotated patterns of retained factors' loadings. These loadings show that, except for two unique (**Domestic-Refuse** and **Cost Reduction**) variables and a complex one (**Exchange**), each variable is highly loaded-on by only one factor, with remaining factors being insignificant. Similarly, each factor loaded highly on a few (5-6) variables while loading insignificantly on many remaining variables.

Following the usual convention for labeling factors by most significant variable, we name and describe the factors (i.e., the identified OFM approaches) as follows:

1. **OFM Approach 1 (Augmentary Compost Use Approach):** Table 4 shows that the first factor loads on six of the organic fertilizer management variables: *Prepare compost in a pit. Apply compost on my farm. Constructed a pit for decomposing animal and household waste into natural manure. Apply organic because it supports the soil for mineral fertilizer to work well. Apply organic fertilizer because I am not able to apply enough mineral fertilizer. Arrange for crop residues from other places after harvesting, which add to mine for use.* These actions/decisions together describe a planned preparation of compost under controlled decomposition of biomass in constructed pits. The most critical variable (lead determinant) on this factor is **Complement-mineral** - *Apply organic fertilizer to help the*

soil for mineral fertilizer to work well. It means that farmers who adopt this approach mostly aim at strengthening soil physical properties to enhance the uptake of nutrients from mineral fertilizers. They are also influenced by the need to supplement mineral fertilizer. Thus, the motivation for using organic fertilizer here is both to complement and supplement mineral fertilizer use. Farmers in this category seem to know that the quantity of mineral fertilizer they apply is insufficient; hence, they add compost as a supplement as well as to support soil health.

Table 2.4: Rotated factor pattern of loadings on variables of OFM approaches

<i>Variable</i>	<i>Factor1</i>	<i>Factor2</i>	<i>Factor3</i>	<i>Factor4</i>
Complement-Mineral	0.81	-0.13	0.03	-0.06
Cost-Reduction	0.34	0.21	0.16	-0.03
Affordability	-0.13	-0.13	-0.22	0.83
Water-Conservation	-0.23	0.46	0.04	-0.37
Profit	0.17	0.07	-0.07	-0.58
Supplement-Mineral	0.79	-0.02	0.11	-0.03
Any/Mixed	0.18	0.29	0.21	0.49
Compost	0.61	0.18	0.20	0.01
Manure	-0.03	0.11	0.66	0.08
Slurry/Sewage	0.13	0.65	-0.07	-0.07
Animal-Droppings	0.12	0.00	0.59	-0.03
Domestic-Refuse	0.20	-0.09	0.06	0.39
Human-Excreta	-0.01	0.83	0.03	-0.05
Free-Collection	0.18	-0.18	0.21	0.50
Own-Production	0.73	-0.02	0.04	-0.02
Exchange	-0.02	-0.02	0.55	0.48
Purchase	0.00	0.73	-0.01	0.02
Waste-Gathering	0.71	0.00	-0.18	0.01
Keep-Livestock	-0.11	0.02	0.91	0.00
Contract-Herdsman	-0.03	-0.15	0.86	0.00
No-Arrangement	0.04	0.31	-0.03	0.64
Arrange-Residue	0.49	0.27	-0.15	0.00
Arrange-Excreta	0.28	0.51	-0.08	0.07

LR test: independent vs. saturated by pf factoring: $(253) = 2393.21$ Prob ≥ 0.0000 . Note: variables- Organic-Standards and crop-residue were not used in the factor analysis because their observed response was zero (constant) for all respondents. Correlation between factors: 1,2 = 0.38, 1,3=0.23 , 1, 4 = -0.01, 2,3=-0.17 , 2,4=0.0, and 3,4=0.23. Bold values show significant loadings of factors on the various practices (Variables)

- OFM Approach 2 (Urban Human Waste Organic Fertilizer Approach):** Five response variables of farmers' decisions/actions loaded on the next (2nd) factor. These are: *Use toilet/urban waste products on my farm. Buy my organic fertilizer from a commercial source. The main component of organic fertilizer is human waste/excreta. Buy my organic fertilizer from a commercial source. Apply organic fertilizer because it helps crops to resist drought. Arrange with waste disposers to supply me domestic/human waste matter.* The lead decision variable here is **Human-Excreta - Use toilet/urban waste products on**

my farm, meaning that this OFM approach is best identified by the decision to use toilet/sewage matter obtained from urban waste disposal agents; hence, the name "*Urban Human Waste Organic Fertilizer Approach*." The decision/action variables on which this factor (approach) loaded together describe efforts to fertilize cereal plots with urban/human waste. Farmers in this category arrange with dump truck drivers to dispose of the contents of their trucks on their cereal plot at a fee. These farmers seem to know or have had the experience that organic fertilizer enhances the soil's water-holding capacity and thus helps crops to resist drought. Thus, their primary objective of applying organic fertilizer, as indicated by the organic fertilizer use objective named **water conservation**, is to adapt their crop to environmental shocks, particularly droughts.

3. **OFM Approach 3 (Integrated Livestock Manure Approach):** Five decision variables characterize this approach: *Use only farmyard manure as organic fertilizer. The primary material of my organic fertilizer is livestock/poultry droppings. Obtain my organic fertilizer/materials from non-commercial sources by payment in kind. Keep livestock/poultry so that I can get manure to apply on my farm. Contracted herdsmen/poultry farmers to supply me manure.* Together, the variables describe farmers' efforts to maintain regular supply and use of farmyard manure on their cereal plots either by integrating livestock enterprise or establishing supply agreement with reliable manure sources. Being dominated by a sourcing plan decision variable called **Keep-livestock** - *Keep livestock/poultry so that I can get manure to apply on my farm*, we labeled the factor "*Integrated Livestock Manure Approach*". Farmers in this category keep livestock (mostly small ruminants) as a source of farmyard manure besides income generation, while those without livestock establish some relationship with livestock owners who can supply them manure. However, no organic fertilizer use objective is uniquely associated with this management approach.
4. **OFM Approach 4 (Mineral Fertilizer Cost Constraint Organic Approach):** This OFM Approach loaded on six variables, including **Profit** - *It is more profitable to employ organic soil amendment than mineral fertilization* – on which the approach loaded negatively. The other variables are: *Apply any type of organic fertilizer available to me. Secure organic fertilizer/materials from a free source in the community. Obtain organic fertilizer/materials from a non-commercial source (payment in kind). Apply organic fertilizer because I cannot afford mineral fertilizer. Collect organic fertilizer from any locally available source when needed.* These variables are ad-hoc decisions/actions taken

by farmers to use organic fertilizer even though they believe that organic fertilizer is less profitable than mineral fertilizer. Farmers adopt this approach mainly because they cannot buy mineral fertilizer; thus, we labeled this approach "*Mineral Fertilizer Cost Constraint Organic Approach*." The approach is naturally untenable since it is characterized by unplanned use of the input, relying on free sources because the farmer cannot afford mineral fertilizer. For a comparison of how popular these OFM approaches are among farmers, we refer the reader to Table 6, which shows the relative percentage spatial distribution of observed practices associated with the four OFM approaches.

2.4.2 *Characteristics of OFM approaches*

We present the results of characterization regressions in Table 5 below. The table shows socio-economic variables that affect farmers' tendency towards the four OFM approaches (factors). In all, the variables explained 25-58% of the variance in factor scores of the OFM approaches. The Urban Human Waste Organic Fertilizer Approach (Approach 2) is least explained ($R^2 = 0.25$), while the Fertilizer Cost Constraint Organic Approach (Approach 4) is most explained ($R^2 = 0.58$) by the socio-economic characteristics. Coefficients of the equations (Factors 1 to 4) are jointly significant at 1%, 1%, 5%, and 1%, respectively. Equation (1) has a weak but positive correlation (0.3) with equations (2) and (3) (see correlation matrix in Table 2.5). Equation 2 and equation 3 are also weakly but negatively correlated (-0.3), while equation 4 is uncorrelated with any other. A positive correlation means some OFM decisions/actions are common to the approaches such that the adoption of one implies an increased tendency towards the other. A negative correlation indicates opposing OFM decisions/actions; thus, a high tendency to adopt one approach means less to the other.

At least two human capital (household characteristic) variables are statistically significant in each of the estimated factor score regressions. The gender of the household head significantly affects two factors - the Urban Human Waste Organic Fertilizer (Approach 2) and the Integrated Livestock Manure (Approach 3) Approaches, but with different signs of the effect. Though not statistically significant, the same opposite signs are observed between the Augmentary Compost Use (Approach 1) and the Mineral Fertilizer Cost Constraint (Approach 4) Approaches.

While being a male household head is positively related to Approach 2 scores, it is negatively associated with Approach 3 scores. This means male-headed households are more likely to engage in practices related to the Urban Human Waste Organic Fertilizer Approach than female-headed households, while the reverse is valid for the Integrated Livestock Manure Approach. It makes

sense because, in a male-dominated society, men always are at the forefront of the households' interactions with external parties (Sexsmith *et al.*, 2017). By contrast, women generally lack the required social leverage to arrange and source waste from disposal companies. That means small livestock operations, which prevail in the study area, are mostly run by women, even in male-headed households (Kahan, 2013). Hence, female farmers are better placed to exploit livestock manure than urban waste for organic soil amendment.

Except for age being significant at 10% and negatively related to only Approach 4, education and household size have no significant relationship in any of the regressions. Family labor force is statistically significant at 1% and positively related only to Approach 1. It means that households with more farm workforce are more likely to adopt organic fertilizer practices associated with the Augmentary Compost Use Approach than those with less workforce.

Participation in organic fertilizer management-related training is statistically significant and positively related to all OFM approaches. The magnitude of the relationship, however, is greatest in the Augmentary Compost Use Approach. Being significant in all the regressions means that farmers' training on organic fertilizer management is a critical step in promoting organic fertilizer use. The proportion of sample farmers who have had some training related to organic fertilizer management is least in the study zone without a farm technology center (Zone 0).

The presence of technology centers generally enhances farmers' access to both formal and informal training. Nevertheless, an individual's willingness to innovate and attitude towards risk determine whether he/she makes use of available opportunities. Farmers' attitude towards risk is statistically significant at 1% and positively affects OFM Approach 1, but it is not significant in the remaining three regressions. This means that farmers who are risk-takers are more likely to adopt the Augmentary Compost Use Approach than their more risk-averse colleagues. As noted above, willingness to take risks is closely linked to the desire to innovate, which in turn influences the self-selection of farmers who exploit training opportunities and learn to adopt related OFM practices.

Table 2.5: SUR model estimates of characteristics of OFM approaches

<i>Variables</i>	<i>Augmentary Compost Use Approach</i>	<i>Urban Human Waste Organic Fertilizer Approach</i>	<i>Integrated Livestock Manure Approach</i>	<i>Mineral Fertilizer Cost Constraint Organic Approach</i>
Household Characteristics				
Gender	0.08 (0.17)	0.34* (0.18)	-0.29* (0.17)	-0.22 (0.14)
Age	-0.00 (0.00)	0.00 (0.01)	-0.00 (0.01)	-0.01* (0.00)
Age Squared	0.00 (0.00)	0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Education	-0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.01 (0.01)
Household size	-0.03 (0.02)	0.01 (0.02)	-0.01 (0.02)	-0.02 (0.01)
Household force	0.06*** (0.02)	0.02 (0.02)	0.01 (0.02)	0.02 (0.02)
Training	0.85*** (0.12)	0.73*** (0.13)	0.21*(0.12)	0.19** (0.10)
Risk attitude	0.05*** (0.02)	0.01 (0.02)	-0.01 (0.02)	0.02 (0.01)
Crop diversity	-0.01 (0.11)	-0.20* (0.12)	0.04 (0.11)	-0.17* (0.09)
Resource Endowment				
Farm assets	0.01** (0.01)	0.01(0.01)	0.00(0.01)	0.00(0.00)
Non-farm incom	0.08 (0.18)	0.19(0.19)	-0.20(0.18)	-0.12(0.15)
Livestock size	0.01 (0.01)	-0.00(0.01)	0.06*** (0.01)	0.00(0.01)
Plot size	0.00 (0.03)	-0.03(0.03)	0.01(0.03)	0.02(0.03)
Institutional/Social Capital				
Beneficiary	0.04 (0.20)	0.19(0.21)	0.00(0.20)	0.10(0.16)
Plot Characteristics				
Min-fertilizer	-0.04 (0.16)	0.16(0.18)	-0.54*** (0.17)	-1.66*** (0.13)
Distance to farm	0.04 (0.06)	0.06(0.07)	-0.01(0.07)	0.09*(0.05)
Land tenure	-0.15 (0.25)	-0.21(0.27)	-0.05(0.25)	0.08(0.20)
Soil Quality rate	0.02 (0.09)	0.11(0.10)	0.04(0.09)	0.09(0.07)
Zone 0 (Bunkp)*	-	-	-	-
Zone 1 (Langbensi)	0.86*** (0.22)	0.30(0.23)	0.54** (0.22)	0.01(0.18)
Zone 2 (Garu West)	0.74*** (0.20)	0.55** (0.22)	0.23(0.21)	0.07(0.16)
Zone 3 (Garu East)	0.60*** (0.18)	-0.13(0.19)	0.01(0.18)	-0.23(0.15)
Constant	-1.26*** (0.36)	-0.92** (0.39)	0.07(0.36)	1.28*** (0.29)
Observations	250	250	250	250
R ²	0.36	0.25	0.33	0.58
Error's matrix of ρ	Approach 1	Approach 2	Approach 3	Approach 4
(Σ)				
Approach 1	1			
Approach 2	0.3	1		
Approach 3	0.3	-0.3	1	
Approach 4	0.1	0.1	0.1	1

B-P test of independence: (6) = 63.147, Prob > = 0.0000.

*Note: Age Squared is a quadratic term for Age. Observed production purpose was a (0) constant while Household income, Fbo membership & Extension contact were found to correlate strongly (0.95, 0.98) with Farm assets and Beneficiary, respectively, and were consequently dropped from the analysis. Zone 0 (Bunkpurugu) is the reference location (location without technology center). Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. F-statistic tested the joint statistical significance of coefficients in each equation on both OLS and SUR estimates. Differences between coefficients of paired SUR equations were also tested using the Chows test executed by the *suest* command.*

Household crop enterprise diversity index is significant but negatively associated with Approach 2 and Approach 4, both at 10%. It implies that farm households that cultivate many crops are less likely to engage in practices under the Urban Human Waste Organic Fertilizer and the Mineral Fertilizer Cost Constraint Organic Approaches compared to those who cultivate few crops. The value of farm assets is positive and statistically significant (at 5%) only in Approach 1 regression.

This result affirms previous study findings (e.g., Al-hassan, 2009; Kombiok *et al.*, 2012 and Bellwood-Howard, 2013) that capital endowment, especially ownership of farm equipment such as donkey or bullock carts, bi/tricycles, soil rippers, wheelbarrows, and shovels/spades increases the ability of farmers to adopt compost use. Owning donkeys and their carts, in particular, give farmers tremendous leverage over sourcing and transporting materials for compost preparation (Bellwood-Howard, 2013) and might trigger interest in learning how to prepare the input.

Off-farm work participation and farm size, as endowment variables, are not statistically significant in any of the regressions. Livestock size is statistically significant, with a positive effect in Approach 3 regression only. Thus, farmers with higher livestock numbers will tend to engage in organic fertilizer practices related to the Integrated Livestock Manure Approach than those with fewer animals. Participation in soil management policy has a positive but no statistically significant relationship with any of the management approaches.

Some of the plot characteristics (mineral fertilizer, farm distance, and zones) are statistically significant determinants of factor scores in some regressions. The monetary value of mineral fertilizer applied per hectare has a statistically significant (at 1%) negative influence in Approach 3 and 4 regressions but no significant effect on Approach 1 and Approach 2 scores. The implication is that farmers who can apply significant amounts of mineral fertilizer on their cereal plots are less likely to engage in practices under both the Integrated Livestock Manure Approach and Mineral Fertilizer Cost Constraint Organic Approach. The distance of a plot from a farmer's home is statistically significant at 10% only in Approach 4 regression with a positive sign. Contrary to the assertion that organic fertilizer is usually applied on plots closer to farmers' homes (e.g., Qaunsah *et al.*, 2001 and Giller *et al.*, 2011), our result indicates that farmers may send organic fertilizer to distant plots for cereal crop production, under compound land and mineral fertilizer constraints. More precisely, cereal plots located far away from a farmer's home are likely to receive organic fertilizer if lack of access to mineral fertilizer compels the farmer to use only organic fertilizer for subsistence production. It is more so in situations where the farmers lack access to home plots.

The geographical location of a farm has a strong relationship with the choice of OFM approach. Relative to Zone 0 (control zone with no organic fertilizer technology center), a farm located within any of the other zones has a highly significant (at 1%) and positive effect in Approach 1 regression. By the magnitude of estimated coefficients, farmers located in Zone 1, followed by those in Zone 2 and Zone 3, respectively, have the highest tendency to adopt the Augmentary

Compost Use Approach (Approach 1). Approach 2 and Approach 3 are positively associated (at 5%) with Zone 2 and Zone 3, respectively, while no zone is statistically more related to the Mineral Fertilizer Cost Constraint Organic Approach than Zone 0. It means that, except for the Augmentary Compost Use Approach, each OFM approach identifies with a particular zone, making location of a farmer the most significant determinant of OFM approach choice than any other characteristic variable. Thus, based on location (i.e., Zone 1 to 4), we showed the prevalence of various OFM approaches by the percentage of farmers in each zone who used practices found under each approach. Table 2.6 shows the relative percentage distribution, by location, of farmers using practices classified under various OFM approaches. This information can help target organic fertilizer use policies to particular zones.

Table 2.6: Percentage spatial distribution of OFM practices by farm location

OFM Decisions/Practices in each Approach	Percentage of Farmers Using Practice				
	<i>Zone 0</i>	<i>Zone 1</i>	<i>Zone 2</i>	<i>Zone 3</i>	<i>Study Area</i>
<i>Augmentary Compost Use Approach</i>					
Compost	30	95	73	52	56
Own-Production	36	88	62	63	59
Complement-Mineral	33	75	62	68	58
Supplement-Mineral	47	79	83	76	70
Waste-Gathering	24	75	51	48	46
Arrange-Residue	24	42	45	40	38
<i>Urban Human Waste Organic Fertilizer Approach</i>					
Slurry/Sewage	9	29	34	20	22
Human-Excreta	4	17	24	14	14
Purchase	5	20	20	4	10
Water-Conservation	42	71	77	52	58
Arrange-Excreta	7	21	23	19	24
<i>Integrated Livestock Manure Approach</i>					
Manure	20	33	24	13	20
Animal-Droppings	18	29	28	20	23
Exchange	62	62	38	29	44
Keep-Livestock	44	62	45	26	40
Contract-Herdsmen	51	71	49	40	50
<i>Mineral Fertilizer Cost Constraint Organic Approach</i>					
Any/Mixed	69	79	72	47	63
Free-Collection	42	4	26	18	28
Exchange	62	62	38	29	44
Affordability	45	8	11	4	17
No-Arrangement	58	45	43	23	40

Note: numbers under zones are percentages of respective zonal sub-samples.

The numbers in the table indicate that OFM Approach 1 dominates in all zones except in Zone 0. Next to OFM Approach 1 practices, OFM Approach 2 practices dominate among farmers in Zone 2. Likewise, after OFM Approach 1, farmers in Zone 1 adopt more of the practices in OFM

Approach 3. By contrast, unsustainable practices of OFM Approach 4 are the most dominant among Zone 0 farmers.

2.5 Conclusion and recommendations

The main objectives of this typological study were to identify organic fertilizer management approaches adopted by smallholder farmers in northeastern Ghana and characterize these approaches by farmer/farming factors that favor their adoption. We used Exploratory Factor Analysis (EFA) to identify the approaches, after which we characterized the approaches using Seemingly Unrelated Regression analysis. EFA identified and named four approaches as; (1) Augmentary Compost Use Approach, (2) Urban Human Waste Organic Fertilizer Approach, (3) Integrated Livestock Manure Approach, and (4) Mineral Fertilizer Cost Constraint Organic Approach. Whereas a set of strategic OFM decisions/actions represents each of management approaches 1 to 3, the Mineral Fertilizer Cost Constraint Organic Approach 4 is identified by ad-hoc decisions/actions regarding organic fertilizer use.

The characterization regressions showed that household labor force, risk attitude, and the total value of farm assets favor the adoption of the Augmentary Compost Use Approach. All geographical locations covered by the study, except the Bunkpurugu zone, also favor this approach. The Urban Human Waste Organic Fertilizer Approach is male-driven and tends to be adopted by farmers specializing in cereal crop production. OFM decisions/actions representing this approach are more likely to be adopted in areas close to city populations like the Garu West. The Integrated Livestock Manure Approach is a livestock enterprise-driven approach and is more favorable to female farmers than male farmers. It is negatively related to the value of mineral fertilizer applied per hectare and has a higher prevalence among farmers located in Langbinsi zone than those in other zones. Compared to the other approaches, the Mineral Fertilizer Cost Constraint Organic Approach 4 appears less strategic: decisions/actions taken by farmers are unplanned and are driven by an inability to access mineral fertilizer. It is widely used in areas where farmers have the least access to training on organic fertilizer use. Contrary to common findings in organic fertilizer literature, this approach is adopted for farm plots further away from farmers' homes. While the first three approaches are worthy of policy support, we note that, with the exception of the Augmentary Compost Use Approach, which is dominant in all zones, the potentials of the approaches to increase organic fertilizer adoption among farmers differ from one location to another.

Though the Augmentary Compost Use Approach has been widely adopted by the majority of farmers in all zones except Zone 0, we recommend that policies focus on supporting farmers to access labor-saving farm equipment for biomass collection, transportation, and pit construction to reduce labor requirement for compost preparation. Besides the Augmentary Compost Use Approach, policy planners should consider supporting the Urban Human Waste Organic Fertilizer Approach in the Sudan Savannah zones. They should target male-headed households with social network capacity programs to link them to waste disposal agencies.

Policies seeking to promote organic fertilizer through the Integrated Livestock Manure Approach should consider supporting the farmers, especially females, to increase livestock sizes and develop skills for collecting manure and other by-products. For such interventions, the farmers should also be educated on the complementary roles organic and mineral fertilizers play in soil health so that they do not substitute one for the other. Lastly, policy designers need to note that training of farmers on organic fertilizer management practices enhances the uptake of organic fertilizer practices under all four OFM approaches. Hence, training of farmers should be a part of any organic fertilizer promotion policy. It is more critical for farmers at places where there is no farm-technology center, and farmers do not have access to any capacity building program.

Finally, a caveat we note is that the study could not identify any organic fertilizer use motivations associated with the Integrated Livestock Manure Approach. This is probably due to exclusion from the objective space, some relevant motives known only to farmers. We suggest widening the space of objectives in future research to include motives such as substituting mineral fertilizer with organic as well as food safety motives. Another way to deepen the research on organic fertilizer use practices in subsequent studies is to assess farmers' behavioral disposition to engage in specific practices characterizing the various management approaches.

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Chapter 3

Organic Fertilizer Practices and Farmers' Attitude: Empirical Insights from Northern Ghana using the attitude-as-behavior model

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Abstract

Using organic fertilizer to improve soil health is essential towards halting the downward trend of yield in Sub-Saharan Africa. However, realizing this goal requires supporting farmers to adopt organic fertilizer practices that match their behavioral inclination and decision-making capacity. This study evaluates farmers' attitude towards organic fertilizer and behavioral costs (difficulty) of a set of organic practices using primary data from farm-households in northeastern Ghana. After applying the explanatory Rasch model to control for scale distortions arising from attitude groupings, the results show that an average farmer's attitude is much less than the average difficulty of the practices, though the practices generally show moderate difficulty. The average attitude strength matches only three of sixteen practices on the scale because most of the farmers (70%) show very weak attitudes towards the input. Latent attitude regression reveals that the weak attitude levels strongly relate to key farmer-background factors, including the level of education, resources owned and access to extension services. Participation in organic fertilizer use policy enhances farmers' knowledge and skills to use the input. Hence, access to such policies can replace education for the less-educated majority of the farmers. Thus, we propose training policies that build average farmer's capacity to adopt, especially the less-difficult practices in the area. Supporting farmers to acquire draught equipment can also facilitate uptake of the difficult organic fertilizer practices and intensify the input's use.

Keywords: *behavioral cost, farmers' attitude, northern Ghana, organic fertilizer practices, explanatory Rasch model*

3.1 Introduction

Governments and other policymakers have recognized the relationship between the fertility crisis and development setbacks of agrarian economies in Sub-Saharan Africa (AfDB, 2006 and Agwe *et al.*, 2007). Soil fertility fundamentally influences agricultural productivity through crop and pasture yields, thus determining farm-households' food supply and incomes (Tittonell and Giller, 2013; and Lagerkvist *et al.*, 2015). This implies that prevailing food insecurity and poverty in the region, where over 80% of rural households depend on farming, are tightly linked to poor soil conditions (Nkonya *et al.*, 2015; and Kim and Bevis, 2019). Therefore, it is reasonable that policies to improve farm productivity and livelihoods of smallholder farmers through soil fertility management underly all national efforts to economic development in SSA (AfDB, 2006).

It is common to conclude that African farmers do not use the required quantities of mineral fertilizer when low crop yield in SSA is under discussion (Chapoto *et al.*, 2015). However, this notion is not simply true because recent increases in fertilizer use for some crops have not shown commensurate yield improvement (Sheahan and Barrett, 2017 and Liverpool-Tasie *et al.*, 2017). The present productivity crisis in the region has much to do with sub-optimal conditions (biophysical and chemical) affecting the overall soil quality rather than just insufficient use of mineral fertilizers (Agwe *et al.*, 2007; Shisanya *et al.*, 2009; Tittonell and Giller, 2013; Lagerkvist *et al.*, 2015; Vanlauwe, 2015). For instance, cereal yields among farmers in the Upper and North East regions of Ghana are stagnating despite increasing mineral fertilizer application (Mellon-Bedi *et al.*, 2020). Additional fertilizer has minimal impact on yield because soils lack organic matter, which conditions effective utilization of nutrients supplied by mineral fertilizers (Tittonell and Giller, 2013; Liverpool-Tasie *et al.*, 2017; and Owusu *et al.*, 2020). Stagnant or falling yield levels imply declining yield to fertilizer-price ratio, which tends to discourage effective fertilizer demand since marginal outcomes of fertilizer suggest farmers apply economically optimal quantities of mineral fertilizers (Liverpool-Tasie *et al.*, 2017).

For yields to respond to mineral fertilizer, making further increase beneficial, farmers must apply significant quantities of organic amendments to revive their soil (Tittonell and Giller, 2013). Organic matter plays a crucial role in balancing chemical and bio-physical conditions of soil, conserving moisture and thus, improving fertilizer utilization by crops (Agwe *et al.*, 2007; Bandanaa *et al.*, 2016; and Kim and Bevis, 2019). Farmers in northern Ghana traditionally have used animal manures and naturally occurring composts within their locality to organically amend soils (Quansah *et al.*, 2001; Fosu-Mensah *et al.*, 2012 and Vanlauwe, 2015). However, these sources are becoming increasingly limited; hence, not every farmer can access them. If they do,

the quantities and quality are usually inadequate for their needs (Tittonell and Giller, 2013; Vanlauwe, 2015; and Wekesah *et al.*, 2019). Thus, they often need to supplement the manures and waste materials with other sources for soils to accumulate adequate carbon.

The government of Ghana, through the Ministry of Food and Agriculture, in partnership with several NGOs, has, for the past two decades, implemented organic fertilizer use projects to support farmers within the four northern regions of the country (Bandanaa *et al.*, 2016). The general purpose of these projects was to increase the quantity, quality, and efficient use of organic amendments by improving 'farmers' traditional management practices. These practices include recycling crop residues by composting and harnessing more manure by increasing livestock numbers, improved housing for animals, and in-stall feeding instead of open-space grazing (Bellwood-Howard, 2013). Farmers have also been sensitized to establish formal relationships with Fulani herdsmen and other livestock owners for manure, agro-processors for their by-products, and waste disposal agents to obtain and use sewage matter or urban waste products (Bellwood-Howard, 2013; Bandanaa *et al.*, 2016 and Kranjac and Gandaa, 2013). Green manuring, agro-forestry, and rotation/intercropping with legumes have also been introduced, even though farmers rarely adopted those (Quansah *et al.*, 2001).

Several agencies, including the Opportunity for Industrialization Center (OIC) and the Presbyterian Agriculture Station (PAS), have trained farmers on pit and heap methods of compost preparation. They have also supported some farmer-groups to procure equipment like donkey carts for gathering materials (Bellwood-Howard, 2013). Agricultural Cooperative Development International/Volunteers in Overseas Cooperative Assistance (ACDI/VOCA) and Alliance for Green Revolution in Africa (AGRA) have also primed farmers on methods of organic fertilizer application, such as the *Zai-pit* method and micro-dosing crops with mineral fertilizers after germination, regardless of the quantity of organic amendment applied.

Consequently, one would expect farmers in the area to use substantial quantities of organic fertilizer after benefiting from the projects. On the contrary, it appears the projects made no impact regarding promoting organic fertilizer use, particularly in cereal production. The input's use is still far below expectations as farmers have not collectively adopted, and many uptakers continue to apply minimal quantities (Bellwood-Howard, 2013).

Attempts to promote organic fertilizer practices (OFPs) without knowing whether or not farmers are inclined to utilize the practices tend to mislead policy efforts (Martey, 2018). For the push towards increasing organic fertilizer use to succeed, the OFPs to be promoted must align with

farmers' attitudes and decision-making capacity (Lagerkvist *et al.*, 2015; and Shikuku *et al.*, 2017). Thus, interventionists need insights from the farmers' perspectives about how they (farmers) tend to engage in existing OFPs to adjust policies in order to make use of farmers' legacy resources and path-dependencies. One intuitive way to gain such insights is to evaluate farmers' attitudes, mapped against behavioral costs (difficulties) for engaging in existing OFPs (Durpoix, 2010). Unfortunately, there has not been any empirical evaluation of farmers' attitudes towards OFPs or assessment of behavioral costs for practices being promoted in Ghana.

Against this backdrop, this study seeks to fill the empirical information gap by 1) evaluating behavioral costs of OFPs and attitudes of farmers towards organic fertilizer and 2) examining farmer-background factors that influence attitude. Adopting Campbell's (1963) behavioral cost-attitude paradigm developed further by Kaiser *et al.* (2010), we followed Lagerkvist *et al.* (2015) and Shikuku *et al.* (2017), by defining organic fertilizer attitude as a 'farmer's *general behavioral disposition* to engage in a set of practices as the means to his/her organic fertilizer objective and applied Rasch/Rasch/Rasch's measurement model on farmers' behavioral responses to a set of OFPs in the northeastern part of Ghana. Unlike the previous studies, however, we used the person-explanatory version of the model that allows incorporating farmer-characteristic variables to control for scale distortions and simultaneously address the objectives (Rijmen *et al.*, 2003; Wilson *et al.*, 2008 and Briggs, 2008). The study contributes to the literature on farmer-attitude assessment in two ways. First, it applies a hybrid version of the recently adopted behavioral cost model (Rasch Measurement) to farmer attitude analysis, thus extending its practical application scope. Second, it provides the first empirical assessment of difficulty (i.e., behavioral cost) and ranking of common OFPs in northern Ghana.

The rest of the paper is structured as follows: Section 3.2 reviews approaches to attitude-behavior assessment, pointing out a drift towards the behavioral cost approach. Section 3.3 highlights the concept of the behavioral approach (Rasch model) to attitude measurement, specifies the empirical model and describes the data used for this study. Section 3.4 presents model estimates and evaluation results, while section 3.5 draws conclusions and recommendations from the findings.

3.2 Farmer attitude assessment: shifting from classical to behavioral approach

The term attitude takes several definitions in the literature and therefore is controversial to use without highlighting contextual meaning. Nevertheless, Eagly and Chaiken's (1993) description of the concept as *a psychological tendency expressed by evaluating a particular entity with some degree of favor or disfavor* resolves much of the controversy (Durpoix, 2010). Yet, a seemingly

different notion of attitude is Campbell's (1963) postulate, refined further by Kaiser *et al.*'s (2010), as *a person's disposition* to carry out a particular behavior. In both conceptions, attitude is abstract and cannot be observed directly; hence it is measured as a latent trait.

Two broad classes of tools for assessing attitudes as a latent trait, following the two concepts, are the classical and the behavioral models. In the classical modeling (CM), analysts use farmers' expressed intentions, affections, or subjective evaluative ratings of aspects of farm technology typically to isolate latent constructs presumed to determine 'farmers' inclination; hence behavior towards the technology under study (Kaiser *et al.*, 2010; and Lagerkvist *et al.*, 2015). Conventionally, studies analyzing farmer-attitude to technology have used CMs like the confirmatory or exploratory factor analysis in examining inclination to new practices (Willock *et al.* 1999; Waithaka *et al.*, 2007; Martínez-García *et al.*, 2013; Shikuku *et al.*, 2013; and Lagerkvist *et al.*, 2015). Though useful for guiding general promotion of farm technology, these models are proven to poorly predict adoption behavior because of functional gaps between constructs and actual behaviors (Campbell, 1963 and Kaiser *et al.*, 2010; and Lagerkvist *et al.*, 2015). The gaps occur because CMs ignore information on the behavioral cost (difficulty) of engaging a practice, which is a direct determinant of actual behavior (Kaiser *et al.*, 2010).

On the contrary, the behavioral cost models postulate a direct link between attitude and actual behavior after accounting for forces opposed to behavior. The opposing forces may include conflicting social norms, religious beliefs, perceived behavioral controls, physical and financial constraints. Collectively, these are referred to as *behavioral cost* or *difficulty* of a behavior (Campbell, 1963; Kaiser *et al.*, 2010; Lagerkvist *et al.*, 2015 and Shikuku *et al.*, 2017). The intuition from the postulate is that, though both intentions and behavior emanate from a person's disposition, behavior does not occur unless after the person is able to pay the cost (i.e., overcome the difficulty) associated with the behavior. In other words, though behavior manifests attitudes, the manifestation would not occur when the cost of behavior exceeds the underlying attitude strength. Thus, a behavior has a 0.5 probability of occurring when attitude strength equals the cost of behavior. Thus, attitude is inferable from observed behavior by a probability function. Yet, for a broad dimensional technology like organic fertilizer use, the underlying attitude is general and adequately manifests itself in a set of appropriate behaviors relating to critical aspects of the technology's performance rather than in a single action (Kaiser *et al.*, 2010).

Following Kaiser *et al.* (2010) seminal exposition of the behavioral cost approach, Lagerkvist *et al.* (2015) applied the Rasch model in comparison with the classical latent construct model in assessing farmers' attitudes to sustainable intensification practices. Their study found that attitude

estimates from these models have entirely different distributional properties, with a moderate correlation coefficient. The behavioral model showed generally weaker attitude estimates in several clusters across the scale but retained more technology set behaviors than the classical model. The classical, on the other hand, gave a relatively high but single-clustered attitude distribution (Lagerkvist *et al.*, 2015). They concluded that the difference reflects a gap between attitude measured through verbal rating and behavior since the behavioral model is more sensitive and retains behaviors that reflect all critical aspects of packaged technology than the classical model. By mapping farmers' attitudes and difficulties of practices on the same logit scale, the model also allows analysts to identify persons and practices that require a policy to facilitate the adoption of a composite technology (Boone, 2016). These make the Rasch model preferable to classical models, considering development agents' current need to accurately target beneficiaries when upscaling up innovations (Parvan, 2011 and Shikuku *et al.*, 2017).

However, the Rasch model only calibrates a logit scale for simultaneous ranking of behaviors and persons. It does not provide any information to explain attitude or difficulty estimates (Rijmen *et al.*, 2003; and Briggs, 2008). Besides a lack of explanatory information, the basic Rasch model's assumptions are often unrealistic for observational settings relying on reported farmer practices (Briggs, 2008; Karami, 2012; and Opariuc-Dan *et al.*, 2017).

For instance, local independence practices become invalid when systematic groups of sample farmers behave differently at a practice: a condition known as differential item functioning (DIF). DIF occurs when different classes of farmers (e.g., males and females) have different probabilities of engaging in a behavior (Karami 2012; Khalid and Glas 2013; and Opariuc-Dan *et al.* 2017). It happens either because the behavior is technically biased against one group or the groups belong to different attitude distributions (Briggs, 2008; Karami, 2012; and Opariuc-Dan *et al.*, 2017). In order to retain objectivity of attitude scale, separate difficulty parameters are estimated for DIF groups due to bias (see Khalid and Glas 2013 and Lagerkvist *et al.*, 2015). On the other hand, if attitude distributions follow the farmer grouping factor, DIF can be resolved by conditioning attitudes on the group variable.

Conditioning attitudes on farmer-background factors should be conventional in examining farmers' attitudes in Africa where economic and cultural circumstances together with beliefs shape farmers' disposition to farm-technology (Shiferaw *et al.*, 2009). A long strand of literature on the link between farmer factors and uptake decisions exists (see Shiferaw *et al.*, 2009; and Fosu-Mensah *et al.*, 2012). Background conditions determine farmers' attitudes through their farm goals, beliefs, and perceptions about the triability of a technology. These, in turn, influence the

probability of behavior (Ridgley and Brush, 1992; Shiferaw *et al.*, 2009; Parvan, 2011; Chikowo *et al.*, 2014; Borges *et al.*, 2015; and Abebe and Debebe, 2019). By drawing implications from Tay *et al.* (2013), differences in farmer-attitudes, determined by background factors, are more likely to cause DIF in observed farmer-behaviors than OFPs bias towards some farmers. It is especially so when a significant proportion of the technology-set practices shows DIF (Khalid and Glas, 2013).

In the generalized linear mixed model (GLMM) setup, different extensions of the Rasch model exist for relaxing invalid assumptions and for incorporating farmer-background information to explain attitude (Opsomer *et al.*, 2003; Rijmen *et al.*, 2003; Briggs, 2008; and Tay *et al.*, 2013). However, the previous attitude studies applied the basic Rasch model and estimated separate difficulty for farmer-groups where practices show DIF, as though such OFPs were biased (i.e., Lagerkvist *et al.*, 2015 and Shikuku *et al.*, 2017). Besides, analysts reverted to an entirely different model to explain farmer behavior by constructing an overall-adoption index and regressing it on farmer characteristics (see Shikuku *et al.*, 2017). Even though this approach is similar to Briggs' (2008) two-step procedure for explaining subjects' trait levels, it leads to information loss. The information loss could be avoided by using the explanatory Rasch (**latent regression**) model to simultaneously achieve the objectives (Opsomer *et al.*, 2003; Briggs, 2008 and De Boeck *et al.*, 2016). The hybrid model resolves DIF while controlling for attitude heterogeneity among the farmers by regressing farmers' attitude scores on their characteristics in the random-parameter GLMM setup. Thus, it gives more realistic estimates than the basic Rasch model (De Boeck *et al.*, 2016).

From our discussion above, it is reasonable to argue that using explanatory Rasch is more appropriate for assessing farmers' attitudes from observed behaviors than the basic Rasch model. In this study, we assume DIF exhibit by some OFPs is due to *impact* of farmer-characteristic groups on attitudes, meaning that the group variables are the determinants of attitudes (Rijmen *et al.*, 2003; Karami, 2012; and Opariuc-Dan *et al.*, 2017). Hence, we adopted the person explanatory Rasch model to evaluate and explain the farmers' attitudes.

3.3 Methodology

3.3.1 The concept of attitude-as-behavior (Behavioral approach)

For farmers under the same farming circumstances, facing a set of distinct OFPs, each practice is an appropriate organic fertilizer behavior that any farmer may choose to engage in. These behaviors manifest, individually, some components, but together a broad unidimensional organic fertilizer attitude. Every behavior occurs at a behavioral cost, generally referred to as *difficulty*

(Lagerkvist *et al.*, 2015; and Shikuku *et al.*, 2017). Behavioral costs differ from one behavior to another within the OFPs set. Subsequently, we shall refer to behavior and behavioral cost as practice and difficulty, respectively. A practice has a 0.5 probability of occurring when attitude equals difficulty of the practice. A farmer purposely chooses to engage in some or none of the behaviors to realize his/her organic fertilizer objectives, for that matter, manifesting his/her organic fertilizer attitude (Ridgley and Brush, 1992; Kaiser *et al.* 2010; Lagerkvist *et al.*, 2015; and Shikuku *et al.*, 2017).

The total number of OFPs that farmer (i) engaged in ($S_i = \sum_{j=1}^J x_{ij}$) is a sufficient statistic to derive his/her organic fertilizer attitude level (θ_i) (Millsap, 2010). Likewise, the number of farmers that engaged in a given practice j , $X_j = \sum_{i=1}^I x_{ij}$ is a sufficient statistic to derive difficulty (δ_j) of the practice. Then practices can be transitively ordered by their difficulty, independent of farmers (Kaiser *et al.*, 2010; and Wang *et al.*, 2014). Hence, farmers also differ by their attitude measures, independent of practices (Kaiser *et al.*, 2010; and Bond and Fox, 2015). Persons with strong attitudes are more disposed to practices than those with weak attitudes (Kaiser *et al.*, 2010; and Lagerkvist *et al.*, 2015).

Thus we can infer the attitude level from observed set of practices the person engaged in, using a probability function. For dichotomous behavior outcomes, there is a real-value attitude measure, θ_i for each farmer, and difficulty measure, δ_j for each OFP. Kaiser *et al.*, 2010 specified the function relating θ_i and δ_j to the probability of a persons' observed behavior using Rasch's (1960) latent trait model. However, as we noted earlier, farmers might differ systematically in their response to some of the practices. This violates the unidimensionality assumption of the basic Rasch scale. However, the assumption can be relaxed by recasting the model in the generalized linear mixed model (GLMM) framework and controlling for factors influencing θ_i . Figure 3.1 shows a structural representation of the Rasch model in GLMM framework.

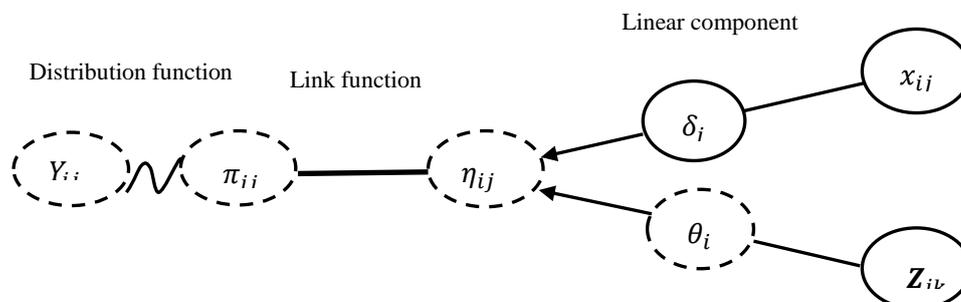


Figure 3.1: Structural representation of Rasch model in a GLMM
Adopted from Wilson *et al.*, 2008

3.3.2 Rasch model specification

From the preceding discussion, a binary state of whether farmer i engages in a given practice (j) follows a probability function of the difference between i 's attitude θ_i and practice j 's difficulty δ_j given as (Kaiser *et al.* 2010; Wang *et al.*, 2014; Lagerkvist *et al.*, 2015 and Shikuku *et al.*, 2017);

$$\Pr(X_{ij} = 1 | \theta_i, \delta_j) = \frac{\exp\{x_{ij}(\theta_i - \delta_j)\}}{1 + \exp(\theta_i - \delta_j)} = \exp(\theta_i - \delta_j), \quad (1)$$

with $j = 1, \dots, J$ practices and x_{ij} is the observed behavior of farmer i for practice j . The log-likelihood L_{ij} of the function is given as;

$$L_{ij} = \ln\left(\frac{P_{ij}}{1 - P_{ij}}\right) = \ln\left(\frac{\exp(\theta_i - \delta_j)}{1 + \exp(\theta_i - \delta_j)}\right) = \theta_i - \delta_j, \quad (2)$$

Attitude is distributed as $\theta \sim N(0, \sigma^2)$ while OFPs are independent and contribute equally to manifesting farmers' attitudes at all levels (equal discrimination). This implies that the probability of engaging in any practice is contingent only on the farmer's attitude level (θ_i) and difficulty (δ_j) of the practice (Opsomer *et al.*, 2003 and Wang *et al.*, 2014). The joint likelihood of a set of practices (\mathbf{S}_i) farmer i engaged in is;

$$L_i(\boldsymbol{\delta}, \theta_i | \mathbf{S}_i) = \prod_{j=1}^J \Pr(x_{ij} = 1 | \theta_i, \delta_j), \quad \mathbf{S}_i = (x_{ij})_{j=1, \dots, J} \quad (3)$$

Assuming farmers attitudes θ_i are fixed for individuals, constraining difficulty δ_j of one practice at 1, or their sum ($\sum_{j=1}^J \delta_j$) at 0, while maximizing the likelihood function on the scores (\mathbf{S}_i), we can obtain a consistent vector of difficulty estimates for the OFPs' (Hardouin, 2007; and Zheng and Rabe-Hesketh, 2007). Also, since $\mathbf{S}_i = \sum_{j=1}^J u_{ij}$ is a sufficiency statistic on θ_i , unbiased estimates of θ_i can also be obtained through a weighted likelihood estimator by maximizing the quantity;

$$\hat{\theta}_s = \max_{\theta} \frac{\exp(s\theta)}{\prod_{j=1}^J (1 + \exp(\theta - \delta_j))} \sqrt{I(\theta)}, \quad s = 0, \dots, J \quad (4)$$

With $I(\theta)$ being the information function, given as $I(\theta) = \sum_{j=1}^J \frac{\exp(\theta - \delta_j)}{\{1 + \exp(\theta - \delta_j)\}^2}$.⁴

Given the vectors $\delta_1, \dots, \delta_J$ of difficulty for practices from equations (3) and persons' attitudes $\theta_1, \dots, \theta_N$ from equation (4), we can rank the OFPs by difficulty independent of farmer-attitude, and likewise the farmers by attitude, θ level, independent of OFPs (Hardouin, 2007; Kaiser *et al.*, 2010 and Rabe-Hesketh & Skrondal, 2012). However, this local independence assumption is

⁴ We skipped formulae for some statistical steps involved between equations (5) and (6) for want of space. We refer interested readers to Hardouin (2007) for the details.

unrealistic in observation data. Thus, we re-specify the model as an explanatory Rasch model in the generalized linear latent mixed model (GLLMM) framework to relax the assumption (De Boeck, 2016). Thus, equation (1) is re-expressed as;

$$\Pr(Y_{ij} = 1 | \mathbf{x}_{ij}, \mathbf{z}_{ij}, \boldsymbol{\theta}_i, \boldsymbol{\delta}) = \frac{\exp(\mathbf{z}'_{ij}\boldsymbol{\theta}_i - \mathbf{x}'_{ij}\boldsymbol{\delta}_j)}{1 + \exp(\mathbf{z}'_{ij}\boldsymbol{\theta}_i - \mathbf{x}'_{ij}\boldsymbol{\delta}_j)}, \quad (5)$$

where \mathbf{z}'_i is a vector of farmer characteristics = 1, 2, ..., p, $\boldsymbol{\theta}_i$ is a vector of random components constituting the attitude measure of farmer i , \mathbf{x}'_{ij} is a vector of the design matrix of the set of practices, $\boldsymbol{\delta}_j$ as defined in equation 1, and Y_{ij} is the observed outcome of behavior j for farmer i with odd-ratio as a realization from Bernoulli distribution with expectation (π_{ij}) such that it is expressed through a log-linear predictor (η_j) as;

$$L(\pi_{ij}) = \log \frac{P_{ij}}{1-P_{ij}} = \eta_j = \mathbf{z}'_i\boldsymbol{\theta}_i - \mathbf{x}'_{ij}\boldsymbol{\delta}_j \quad (6)$$

A latent regression that defines the relationship between $\boldsymbol{\theta}_i$ and \mathbf{z}_i can be specified. Assuming $\boldsymbol{\theta}_i$ follows a multivariate normal distribution ($\boldsymbol{\theta}_i | \mathbf{z}_i \sim N(\boldsymbol{\tau}'\mathbf{z}_i, \boldsymbol{\Sigma})$, it is redefined as (De-Boeck *et al.*, 2003; Wilson *et al.*, 2008 and Briggs, 2008);

$$\boldsymbol{\theta}_i = \mathbf{z}'_i\boldsymbol{\beta} + \boldsymbol{\varepsilon}_i, \quad (7)$$

where \mathbf{z}_i is as defined earlier, $\boldsymbol{\beta}$ is a vector of fixed $\boldsymbol{\theta}_i$ weights ($\theta_{i1}, \theta_{i2}, \dots, \theta_{ik}$) on characteristic factors to be estimated, whilst $\boldsymbol{\varepsilon}_i$ is a vector of random variations of $\boldsymbol{\theta}_i$ of farmer i from population averages. Equation 7 is specified and linked to 6, forming a two-level model within which respondents (level 2) nest various practices (level-1 units).

Considering findings by previous studies, many farmer-characteristic factors are of interest for their effect on soil management decisions (e.g., Waithaka *et al.*, 2007; Shiferaw *et al.*, 2009; Parvan, 2011; Chikowo *et al.*, 2014; Borges *et al.*, 2015; Abebe and Debebe, 2019; and Mellon-Badi *et al.*, 2020). Kassie *et al.* (2013) grouped these factors as 1) household characteristic factors such as age, gender, educational attainment in the household, participation in non-farm work, organic fertilizer experience, and risk attitude score, 2) social capital factors, including contact with extension agents, farmer-group membership, access to organic fertilizer policy and training opportunities. Physical capital such as ownership of livestock and carting equipment, plot size, and total landholding. Other characteristic variables are land tenure and geographical location.

Conditional on the above farmer-background factors, the data generation process approximates Rasch unidimensional model, such that practices are uncorrelated (local stochastic independence) and do not function differently across farmer-characteristic groups (no DIF). Thus no significant interaction remains between practices and persons; hence interaction terms are not included in the

empirical specification. We specified and estimated the model in the GLLAMM statistical package developed by Zheng and Rabe-Hesketh (2007).

3.3.3 Data and descriptive statistics

The data used for this study was collected through a multistage sampling survey of 250 smallholder farmers from 52 communities across eight districts of the North East and Upper East Regions of Ghana. For the Northeast region, selected communities for the West and the East Mamprusi Districts were clustered around PAS at Lagbinsi, while those chosen for Bunkpurugu and Yunyoo-Nasuan districts were clustered around Bunkpurugu town. In the Upper East region, selected communities for the Tempene and Pusiga districts were clustered around Wurnyanga, while those for Garu and Binduri District were centered between Garu and Binduri towns. The farmers responded to a two-section structured questionnaire during personal interviews (PI). The first section sought information on their background characteristics (see Table 3.1), while the final section elicited data on a set of organic fertilizer practices.

Table 3.1: Farmer/farm characteristic factors and summary statistics

Variable	Description/Measurement	Proportion of sample	
Gender	Dummy: 0 =female, 1= male	0.87	
Age	Age Group1	Dummy :1= 18 - 40yrs (Young), 0 = otherwise	0.48
	Age Group2	Dummy: 1 = 41 - 65yrs (Aging), 0 = otherwise	0.36
	Age Group3	Dummy: 1= ≥65yrs (Aged), 0 = otherwise	0.16
Education	No Educ.	Dummy: 1= no education, 0 = otherwise	0.48
	PrimaryEdu	Dummy: 1= primary education, 0 = otherwise	0.18
	SecondaryEdu	Dummy: 1= secondary education, 0 = otherwise	0.20
	TertiaryEdu	Dummy: 1= tertiary education, 0 = otherwise	0.14
Off-farm work	Dummy: 1 = yes, 0 = otherwise	0.41	
Risk attitude	Risk-averse	Dummy: 1=yes, 0 = otherwise	0.19
	Risk-neutral	Dummy: 1=yes, 0 = otherwise	0.65
	Risk-takers	Dummy: 1=yes, 0 = otherwise	0.16
Organic	Category 1	1 = < 3years, 0 = otherwise	0.11
Experience	Category 2	1 = 3-5years, 0 = otherwise	0.53
	Category 3	1 = >5years, 0 = otherwise	0.36
FG membership	1 = FBO member, 0 = otherwise	0.37	
Policy Benefit	Dummy: 1= beneficiary, 0 = otherwise	0.32	
Extension Contact	1 = has contact with local agent, 0 = otherwise	0.33	
Access to training	Dummy: 1 = yes, 0 = otherwise	0.42	
Carting Equipment	1= owns equipment, 0 = otherwise	0.46	
Livestock Ownership	1 = Owns livestock, 0 = otherwise	0.70	
Mineral fertilizer/acre	Low raters	1= (<100kg), 0 = otherwise	0.25
	Moderaters	1= (100-150kg), 0= otherwise	0.67
	Higher raters	1 = (>150kg), 0 = otherwise	0.08
Landholding	Dummy: 0 = ≤ 5 acres, 1= > 5 acres,	0.29	
Land tenure	Dummy 1 =farmer has the land title, 0 otherwise	0.60	
zone0 (Bunkpurugu)	Dummy: 1 = yes, 0 = otherwise	0.22	
zone1(Langbinsi)	Dummy: 1 = yes, 0 = otherwise	0.26	
zone2 (Garu West)	Dummy: 1 = yes, 0 = otherwise	0.21	
zone3 (Garu East)	Dummy: 1 = yes, 0 = otherwise	0.31	

Note: Risk attitude was obtained by re-coding of Dohmen et al. 's (2005) willingness to take risk self-scores into three categories: risk-averse, risk-neutral, and risk-takers.

Our study identified, from Lagerkvist *et al.*'s (2015) integrated soil fertility management (ISFM) attitude scale, many practices that formed our instrument for an organic fertilizer attitude assessment. After a literature review (e.g., Quansah *et al.*, 2001; Fosu-Mensah, 2012; Kranjac and Gandaa, 2013; and Bandanaa *et al.*, 2016) on OFPs, we adapted the instrument to suit current organic fertilizer technology in the study area. Key stakeholders in organic fertilizer support projects, including management of PAS and ACIDI/VOCA, as well as farmers representatives, validated a set of 20 OFPs that formed the final instrument for the study. Together, these practices (in Table 3.2) adequately represent the empirical range (scale) of farmers' attitudes towards organic fertilizer use in the study area. Farmers reported their behavioral outcomes for the practices in a dichotomous format (i.e., whether they engaged in the practice or not). Appendix 3A shows the distribution of a) farmers' behavioral outcomes and b) odd-ratios of practices.

Table 3.2: Description and summary of organic fertilizer practices in attitude instrument

Organic Fertilizer Practice		Description of Practice	% sample
No	Label		
1	CommuSource	Secure manure/compost from community Kraal/ refuse dump.	58
2	CropResidue	Use of crop residues for compost or plow it into the soil.	40
3*	AgroByProduct	Use of agro by-products as an organic fertilizer.	46
4	ArrangLifstock	Arrangement with larger livestock farmers to obtain manure.	36
5	TravKilometers	Travel several kilometers to convey organic matter or manure.	24
6*	MoblizNeighbor	Mobilize neighbors and friends to help apply organic fertilizer.	48
7	UseTrasport	Own/hire tricycle/donkey-cart to transport organic fertilizer or materials.	35
8	ExtenalResidue	Collect crop residues from external sources for composting.	26
9*	Org_MinCombin	Apply both organic and mineral fertilizers.	98
10	PaveAnimalPen	Pave/litter the floor of animal pen to enhance manure collection.	35
11	HireLabor	Have/Hire labor to collect and apply organic fertilizer.	28
12	MicrodosMin	Apply micro-dose of mineral fertilizers to crops on the organic plot.	42
13	Broadcast&Plow	Broadcast and plow organic fertilizer into the soil.	62
14	Apply_B4plant	Incorporate organic fertilizer into the soil weeks before planting.	24
15*	HeapComposting	Prepare compost by the heap method.	89
16	ZaiPitMethod	Apply organic fertilizer by the Zai Pit method.	26
17	Human-Excreta	Use of human-waste as organic fertilizer.	20
18	PitComposting	Prepare compost in a constructed pit.	17
19	DisposalAgent	Source organic soil fertilizer from a waste disposal agent.	12
20	DecomposeB4	Decomposition of all organic matter (biomass) before applying it.	61

Note: dichotomous answers (Yes or no) measured response to all items. Asterisk () indicates item did not fit the Rasch scale; hence, we removed such items from the final scale calibration*

Factor analysis of the data to ascertain dimensionality of the attitude underlying the OFPs (Millsap, 2010) showed only one significant factor, with an eigenvalue of 4.1, explaining 76% of the total variance in the data. The next factor had an eigenvalue of 0.82 but with only one significant loading. The proportion of total variance explained by the first factor is about 5-times that of the subsequent factor, showing a sharp break between them (see Appendix 3B and 3C). This implies that the trait represented by the first factor is the only latent variable and approximates

a Rasch unidimensional construct in the data (Linacre, 2009; Slocum-Gori and Zumbo, 2011; and Hasmy, 2014)

3.4 Results and discussion

In this section, we first show the calibrated Rasch scale results (CML descriptive Rasch model). Then, we present and discuss the explanatory model results compared to the random-effect descriptive Rasch model. We present each of these under a separate sub-section below.

3.4.1 Rasch measurement model and fit indexes

The initial model fitted by either the marginal maximum likelihood (MML) or conditional maximum likelihood (CML) estimator showed that four (practices 3, 6, 9, and 15) out of 20 did not fit the Rasch measurement model. Their fit indexes indicate they either do not contribute to attitude (i.e., 9 and 15) or farmers misunderstood the statements eliciting response for those practices during the survey. Thus we considered such items as distractors (Linacre, 2009) and consequently removed them to improve the calibrated scale. Table 3.3 shows CML difficulty (δ) estimates and fit indices of the 16 practices retained by the scale, while figure 3 shows the scale *Infit* and *Outfit* indexes of farmers, respectively.

Table 3.3. Difficulty (δ) estimates of practices by descriptive Rasch measurement model

No	OFP Label	Difficulty (δ)	S E	R_{1c} Test Statistic	df	p-value	Standardized		U-tests
							Outfit	Infit	
13	Broadcast&Plow	-2.01***	0.23	0.14	2	0.93	0.75	0.24	0.39
20	DecomposeB4	-1.94***	0.23	4.77	2	0.09	1.89	2.64	1.65
1	CommuSource	-1.73***	0.22	1.90	2	0.39	-0.67	-0.05	0.01
12	MicrodosMin	-0.85***	0.22	0.43	2	0.81	0.5	0.2	-0.08
2	CropResidue	-0.73***	0.22	1.35	2	0.51	-1.19	-1.41	-0.83
4	ArrangLifstock	-0.57***	0.22	0.84	2	0.66	-0.08	0.26	0.52
10	PaveAnimalPen	-0.48***	0.23	5.88	2	0.05	1.39	0.12	0.08
7	UseTrasport	-0.45**	0.23	9.56	2	0.01	0.63	1.37	1.64
11	HireLabor	0	fixed	0.96	2	0.62	0.38	1.28	0.93
8	ExtenalResidue	0.08	0.23	0.77	2	0.68	-0.43	0.48	-0.12
16	ZaiPitMethod	0.11	0.23	0.72	2	0.70	-0.59	-0.23	-0.15
5	TravKilometers	0.22	0.24	0.14	2	0.93	1.12	0.47	-0.16
14	Apply_B4plant	0.25	0.24	1.10	2	0.58	-1.01	-0.9	-0.67
17	Human-Excreta	0.52***	0.24	6.10	2	0.05	-1.87	-1.57	-1.27
18	PitComposting	0.79***	0.25	1.61	2	0.46	-1.78	-1.72	-1.52
19	DisposalAgent	1.36***	0.27	1.89	2	0.39	-1.16	-1.75	0.42
R1c test: (data fit)			R1c= $\chi^2(44.7)$	df =30	p-value 0.3413				
Andersen LR test: (invariance)			Z= $\chi^2(49.2)$	df =30	p-value 0.0150				

The null hypothesis (H_0) for R_{1c} tests: the difficulty of very practice is locally independent of attitude level.

, * denote significance at 5% and 1%, respectively. δ for HireLabor is set at zero for identification.

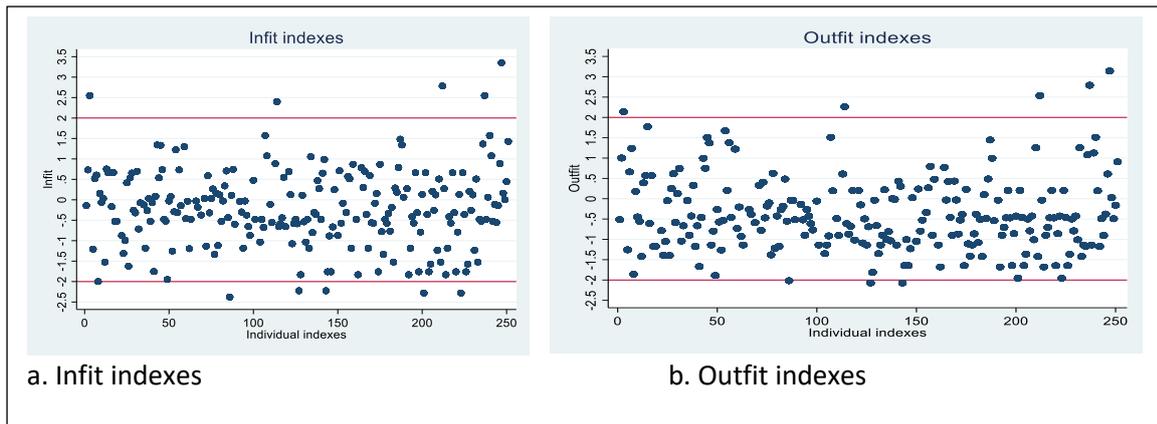


Figure 3.3: Farmers' (a) infit and (b) outfit indexes for the Rasch measurement model

Likelihood ratio test ($\chi^2 = 27.76$, $DF=22$, $p= 0.213$) of fit comparing the primary Rasch model with a unidimensional two-parameter model rejected the assumption that the two-parameter model fits better than the primary model. This affirms the U-test statistics for individual practices, all of which are within the expected range of ± 1.99 (-1.52 to 1.65), confirming the Rasch model assumption that no OFP significantly discriminates between attitude-levels of farmers more than others. We then assessed practices for differential item function (DIF) across farmer-characteristic groups using the logistic regression test (Kleinman and Teresi, 2016). No practice showed significant DIF across gender groups. Practice 10 (**PaveAnimalPen**) exhibited significant DIF across farmers of zone 1 and the rest, while practice 17 (**Human-Excreta**) showed significant DIF for farmers of zone 2. Practice 7 (**UseTransport**) functioned differently across off-farm work participation groups, while practice 20 (**DecomposeB4**) exhibited DIF across organic fertilizer policy beneficiary groups. To the extent that these characteristics influence attitudes, the observed practices of farmers will vary, making the assumption of local independence practices unrealistic (Briggs, 2008). Figure 3.4 is the farmers-practices map, showing attitudes (score) level distribution and difficulty level grouping of the practices (items) on the calibrated logit scale.

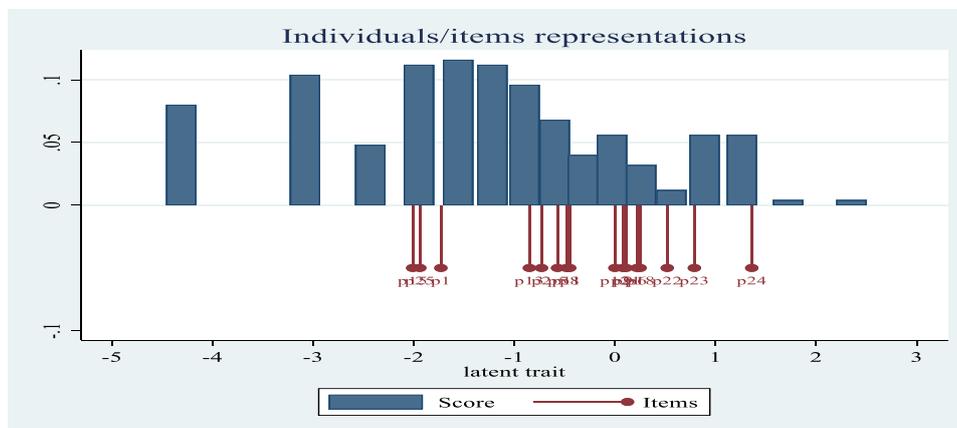


Figure 3.4: Farmers-Practices Map on Rasch Scale

3.4.2 Explanatory Rasch (latent regression) model results

In order to establish a basis to adjust the attitudes for effects of background factors, we fitted a random parameter logistic Rasch model (Descriptive mixed Logit-DML) before the hybrid Explanatory Mixed Logit (EML) model (Rijmen *et al.*, 2003 and Briggs, 2008). Table 3.4 presents the DML estimates in the main column 2, while those of the EML are shown in the last main column. The results showed that the order of practices by their difficulty (δ) remained the same in all models. To **Broadcast&plow** *organic fertilizer into the soil* is the least difficult organic fertilizer practice (behavior), while **DisposalAgent-** *arrange with waste disposal agents* for organic fertilizer is the most difficult practice for the farmers. After adjusting by the mean effect (-1.03 logits) of farmer characteristics, the EML model gave the narrowest net range of difficulty estimates (-1.01 to 2.36) between the lower end of the CML and the upper end of DML model estimates. The EML also gives smaller standard errors, closer confidence interval, and overall best model fit, thus providing the most precise parameter estimates. The results suggest that the CML Rasch model tends to underestimate, whilst the unconditional mixed-logistic model (the DML) overestimates the difficulty of practices compared to the hybrid model. This finding agrees with Rijmen *et al.* (2003) and Briggs (2008), that if the trait being measured follows a mixture of distributions along farmer-characteristic groupings, estimates obtained by CML are inconsistent. Therefore, we present and discuss the OFP ranking based on the EML model estimates.

3.4.3 OFP difficulty and farmer attitude measures

The difficulty estimates in Table 3.4 (under **Adjusted**) show only three relatively easy (negative difficulty) organic practices for the sampled farmers. These are *Broadcast and plow organic fertilizer into the soil*, *Decompose organic matter before using it as organic fertilizer*, and *Securing manure/compost from local community refuse dump/Kraals*. These are organic fertilizer practices having uptake probability of 0.5 or more by even farmers with below-average attitudes, implying that average and above-average attitude level farmers easily carry out such OFPs. The remaining 13 practices are at the difficulty side of the scale but also in three distinct difficulty groups: "slightly-difficult", "difficult", and "very difficult." Practices such as *Apply organic fertilizer with micro-doses of mineral fertilizer*, *Use crop residues*, *Arrange with livestock farmers to obtain manure*, *Pave or litter the floor of the animal pen to enhance the collection of manure*, and *Hire a tricycle/donkey cart for transporting organic fertilizer/materials* constituted the "slightly difficult" group

Table 3.4: Generalized linear and latent mixed model estimates of DML and EML Rasch models

		DML Rasch Model			EML Rasch (Latent regression) Model			
Code	Practice	Est. (δ)	Error	p> z	Est. (δ)	Error	p> z	Adj. (δ)
13	Broadcast&Plow	-0.72***	0.16	0.000	-2.01***	0.13	0.000	-1.01
20	DecomposeB4	-0.65***	0.16	0.000	-1.94***	0.13	0.000	-0.94
1	CommuSource	-0.45***	0.16	0.017	-1.73***	0.13	0.007	-0.73
12	MicrodosMin	0.43***	0.16	0.008	-0.81***	0.13	0.012	0.19
2	CropResidue	0.54***	0.16	0.001	-0.70***	0.13	0.001	0.30
4	ArrangLifstock	0.70***	0.16	0.000	-0.53***	0.13	0.000	0.47
10	PaveAnimalPen	0.80***	0.17	0.000	-0.44***	0.13	0.000	0.56
7	UseTrasport	0.82***	0.17	0.000	-0.41***	0.13	0.000	0.59
11	HireLabor	1.27***	0.18	0.000	0.04**	0.02	0.017	1.04
8	ExtenalResidue	1.36***	0.18	0.000	0.12**	0.06	0.015	1.12
16	ZaiPitMethod	1.38***	0.18	0.000	0.15***	0.07	0.000	1.15
5	TravKilometers	1.50***	0.18	0.000	0.26**	0.11	0.016	1.26
14	Apply_B4plant	1.53***	0.18	0.000	0.29***	0.15	0.000	1.29
17	Human-Excreta	1.80***	0.19	0.000	0.55***	0.16	0.000	1.55
18	PitComposting	2.07***	0.20	0.000	0.81***	0.17	0.000	1.81
19	DisposalAgent	2.64***	0.23	0.000	1.36***	0.20	0.000	2.36
Latent attitude (θ) regression								
Characteristic variable					Coeff. (β)	Std. err.	Adjusted β	
Gender					-0.026	0.15	-0.021	
AgeGroup2					-0.011	0.11	-0.009	
AgeGroup3					-0.208	0.16	-0.166	
PrimaryEdu					0.077	0.14	0.061	
ScondaryEdu					0.331*	0.17	0.264	
TertiaryEdu					0.371**	0.16	0.296	
HHLabforce					-0.024	0.03	-0.019	
Non-Farm Work					-0.178	0.14	-0.142	
Risk-neutral					-0.213	0.24	-0.140	
Risk-takers					-0.931***	0.10	-0.743	
OrgeExp_Categ2					-0.076	0.16	-0.061	
OrgeExp_Categ3					-0.442**	0.18	-0.353	
PolicyBenefit					0.772***	0.16	0.616	
ExtenContact					0.493***	0.18	0.393	
LivestockOwn					0.236***	0.04	0.188	
MinFertClas2					0.091	0.16	0.073	
MinFertClas3					0.135	0.12	0.108	
CartEquipt					0.220*	0.12	0.176	
Landholding					-0.270***	0.10	-0.215	
LandTenure					0.306**	0.14	0.244	
AccessTraining					0.525***	0.13	0.419	
Langbinsi Zone 1					0.407**	0.16	0.325	
Garu West Zone 2					0.282*	0.16	0.225	
Garu East Zone 3					0.211	0.15	0.168	
Const.					1.439***	0.07	-0.363***	
Variance (θ)					1.57***	0.21	0.132***	
Reliability ($1 - \frac{\bar{\sigma}_p^2}{var(\theta)}$)					0.89		0.92	
Log-likelihood					-2057.98		-1883.11	
IC					AIC	4149.12	3842.22	
					BIC	4256.51	4081.39	
Observations					4000		4000	

LR test: DML nested in EML-Latent regression $\chi^2(23) = 359.91, Prob > \chi^2 = 0.0000$

*** p<0.01, ** p<0.05, * p<0.1. FG membership correlated strongly (0.95) with Policy benefit; hence it was dropped.

Note: we left out AgeGroup1, No Education, risk-averse, Organic Exp_Categ1, minfertCategory1 and Zone 0 as base-categories and to avoid dummy variable trap. $\bar{\sigma}_p^2$ is the calculated variance of the predicted farmer θ levels.

Similarly, *Have/hire labor for collection and application of organic fertilizer*, *Collect crop residues from other places after harvesting for compost*, *Apply organic fertilizer by the Zai-pit method*, *Travel several kilometers to convey organic matter/ manure for use*, and *Incorporate organic fertilizer into soil weeks before planting* are in the "difficult" group of practices. The "very difficult" OFP group includes *In-pit preparation of compost*, *Use human-waste as organic fertilizer*, and *Source organic fertilizer from waste disposal agent*. These are practices that even the farmers with the strongest attitude in the sample require external support to enable them to adopt.

Location of farmers (θ values) on the scale range from a lowest of $\theta = -3.8$ to a highest of $\theta=1.6$ logits with the mean $\theta = -0.93$ logits. Seventy percent (70%) of the farmers have attitude estimates of less than zero (see figure 3.5), about $\frac{3}{4}$ of whom have less than the negative sample mean attitude level. Thus, based on the three attitude classes tested in the scale, we label the groups as "very weak", "weak" and "moderate". Given the mean difficulty (0.69 logits) of practices, an average sample farmer attitude level is about 1.62 logits less than required to have a 0.5 probability of engaging in a slightly difficult practice like *hiring a vehicle to transport organic fertilizer*. Farmers with the strongest attitude ($\theta = 1.6$ logits) can overcome ($\theta > \delta$) difficulties of 11 practices, meaning that five (5) practices have difficulty levels beyond any sample farmer's attitude strength. This indicates a generally weak farmer-attitude against the practices.

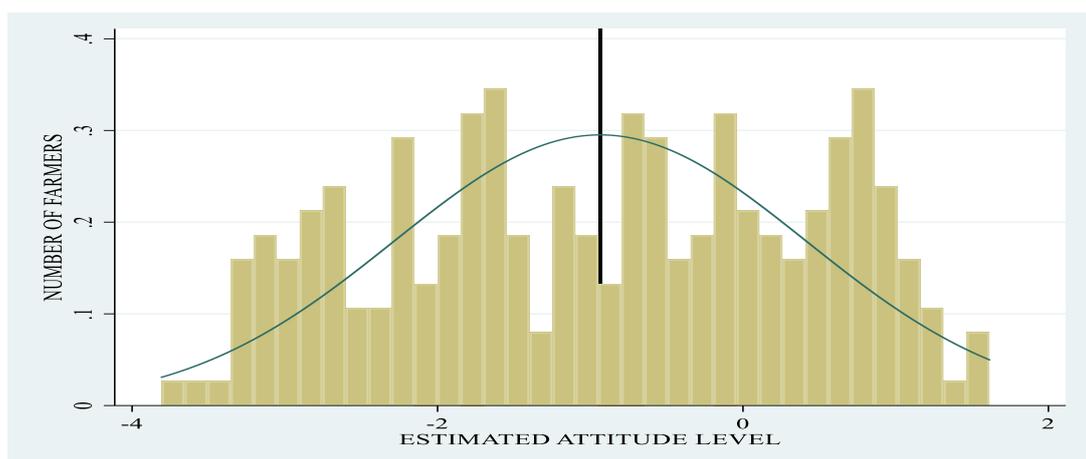


Figure 3.5: Expected a posteriori (EAP) attitude scores of farmers

3.4.4 Determinants of organic fertilizer attitudes

The lower part of Table 3.4, under the EML model, reports the results of latent attitude regression on farmer-background factors. For purposes of interpretation, we divided the logit coefficients

(*Coeff. (β)*) by the standard deviation of EAPs derived from the DML model to obtain effect-size (in z-scores) coefficients under *Adjusted β* . Thus, we discussed the relationship between attitudes and farmer-characteristics using the z-score standardized coefficients.

Gender, age, and primary education relative to no education have no significant relationship with variation in farmers' attitudes towards OFPs. However, farmers who had secondary and tertiary education are +0.26 and +0.30 z-scores, respectively, away from an average farmer attitude level. This result is in line with Kassie *et al.*'s (2015) findings that farmers appreciate the need to use organic fertilizer if they fully understand the nexus between soil health and organic practices. Farmers who attained high educational levels are more predisposed to organic fertilizer than those with low education because the information needed to facilitate understanding and make them inclined to organic fertilizer is better accessed by the highly educated ones. Farmers who benefited from soil management policies are about 0.62 z-scores more inclined to engage in organic fertilizer practices than an average sample. This is not surprising because, through such programs, they have acquired knowledge, skills, and physical resources that predispose them to the input's use.

Surprisingly, household labor force and off-farm work have no significant relationship with farmers' attitudes. These are contrary to expectation, given the common assertions that organic fertilizers are naturally bulky, requiring much human effort to gather, transport and apply (Zingore *et al.*, 2007).

Risk-takers tend (-0.74 z-scores) less to organic fertilizer practices than risk-averse. For risk-averse farmers, conservational benefits and local availability of organic fertilizer could induce reliance on it (Vanlauwe, 2015). On the contrary, risk-takers invest both time and money towards mineral fertilizer access (Duflo *et al.*, 2011), thus may tend less to organic fertilizer. Another surprisingly contrary finding to our expectation is that farmers who applied organic fertilizer consecutively more than five seasons exhibit (-0.35 z-scores) less tendency to organic fertilizer use, relative to those with three or fewer seasons of application. It is likely that farmers become less inclined to use organic fertilizer as their soils accumulate a significant amount of organic matter, or through experience, they identify one or few less-difficult OFPs to rely on for their organic fertilizer need.

Livestock ownership positively covaries with farmers' organic attitudes. Livestock owners have access to manure, which they use even if they have enough mineral fertilizers Kassie *et al.* (2015). Total arable land that a farmer possesses is another resource characteristic that negatively covaries with farmer attitudes. Farmers with total arable land exceeding 5 acres have a -0.215 z-score less

attitude than the average sample farmer. Our finding agrees with Holden (2014) that the land scarcity and the consequent need to intensify production influence farmers to use organic fertilizer. Land-constrained farmers tend more to organic fertilizer use than those who are not. Farmers who hold title to their farmland also tend more (+0.24 z-scores) to OFPs than those who use communal or rented plots. This result is not surprising since it has been well established in the literature (e.g., Abdulai and Huffmann, 2014; and Kousar and Abdulai, 2016) that farmers invest in medium to long-term soil improvement if they are sure of reaping the benefits themselves. Participation in soil management training programs positive covariate of farmers' attitude, and farmers who participated in such training show 0.42 more inclination to OFPs than those who did not participate.

Finally, for locations relative to the Bunkpurugu area (reference zone), farmers in Langbinsi and Garu-Tempene areas are more inclined to OFPs. However, farmers in the Binduri area have no significant attitude difference from the reference zone farmers. The observed differences here could be attributed to environmental factors, access to opportunities for training, and soil management support programs.

3.5 Conclusions and Recommendations

This paper set out to evaluate 1) the difficulty (behavioral cost) of various organic fertilizer practices being promoted among smallholder farmers in Northern Ghana, 2) farmers' general attitude to organic fertilizer use and 3) identify farmer-background factors that drive attitudes toward organic fertilizer use. Adopting the behavioral cost approach, we used the explanatory (latent regression) Rasch model, which allowed us to include farmer background characteristics to control for impacts and explain farmer attitudes levels.

Conditional estimates show a moderate difficulty range for practices against a dispersed but generally weak farmer attitude distribution on the scale. A Farmers/Practices map revealed that an average farmer attitude could overcome difficulty levels of only three out of 16 practices, even though the practices, in general, have moderate difficulty. When attitudes are allowed to follow a mixture of normal distributions along farmer-characteristic groups in a random parameter model, the OFPs maintain their difficulty ranks and intervals but shift rightwards to a higher difficulty range on the scale. The spread of attitude estimates on the scale also reduced from both the lower and upper limits. Yet, a large part (75%) of the distribution remained on the negative side of the scale. Together, these results suggest that farmers' failure to use organic fertilizer as expected is

more attributable to weak farmer-attitudes towards the input than the difficulty of practices involved.

Farmer-attitude to organic fertilizer covaries with some influential socioeconomic and environmental background factors. Background factors such as education beyond primary, access to organic fertilizer policies, and soil management training build farmers' capacity by equipping them with knowledge and skills required for organic fertilizer use. Ownership of physical resources such as farmland and carting equipment as well as farmers' physical location relative to Bunkpurugu area are all related to strong attitudes towards organic fertilizer use. On the other hand, background factors such as farmers' risk behavior, farmland, and the number of farm-seasons organic fertilizers have been applied are related to weak farmer-attitudes. However, such a negative relationship, particularly between attitude and organic fertilizer experience, is surprisingly contrary to expectation and requires further investigation to establish practical reasons and potential implications.

Based on farmers' current disposition, a farmer-capacity building policy will be required to accelerate the uptake of the "slightly difficult" OFPs for upscaling organic fertilizer adoption among average farmers. Such policies may focus on social and human resource capacity deficits, specifically relating to practices like *apply organic with micro-doses of mineral fertilizer, use crop residues, arrange with larger livestock farmers for manure, paving or littering animal pen to enhanced manure collection, having/hiring transport to convey organic fertilizer/materials*. Training and information delivery through extension should aim at providing knowledge and skills particularly relevant to these organic practices, especially to farmers in the Bunkpurugu, Langbensi, and Garu-East zones. Furthermore, care should be taken to include the less educated and socially disadvantaged conservative farmers in such capacity-building programs.

For intensification purposes, a policy should consider reducing the difficulty of practices such as *deploying enough labor to collect and apply organic fertilizer, collecting additional crop residues from other places than one's farm, using the Zai-pit method of applying organic fertilizer, conveying organic matter from several kilometers away and incorporate organic fertilizer into the soil weeks before planting*. These practices currently appear "difficult" to farmers, apparently because of pecuniary costs of labor and capital services as the major hindrance. A specific intervention helping farmers to own draught and carting equipment will give them control over the pecuniary cost of the practices and rapidly enhance attitudes towards their uptake.

The challenges associated with the three most difficult practices (i.e., *source organic fertilizer from waste management companies; preparation of compost in designed pits; use of decomposed excreta as organic fertilizer*) will require strategic management. A policy could support the most inclined farmers to help intensify organic fertilizer use and be nucleus farmers, assisting others. For example, supply-chain relationships could be established between individual farmers and waste management companies, using farmers with prior experience as coordinators. Generally, the agricultural extension department should work more towards farmers' sensitization to realize the need to apply organic fertilizer even if they access adequate mineral fertilizers.

Finally, some caveats worth consideration when drawing insights from this study for either a policy or subsequent studies are noted. The predictability of farmers' behavior using conclusions from this study is limited to short-term and spatial dimensions. The findings did not capture attitude changes or behavioral cost variations of OFPs over time because of the cross-sectional nature of the data we used. Also, the person-practice map shows some behavioral cost gaps between practices, indicating that a few more OFPs may be required in the instrument to cover the entire organic fertilizer attitude domain. Yet, some of the OFPs that could match such gaps did not fit the attitude scale, probably because farmers misunderstood the survey questions presented to them.

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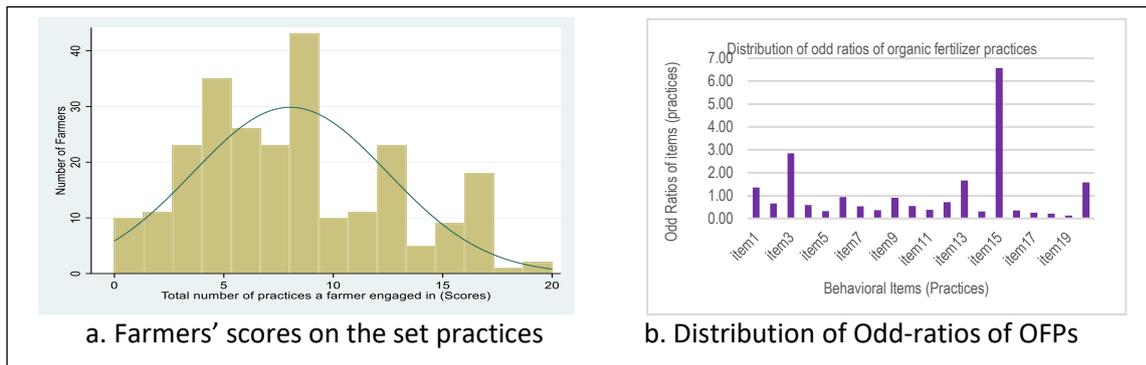
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Appendices 3



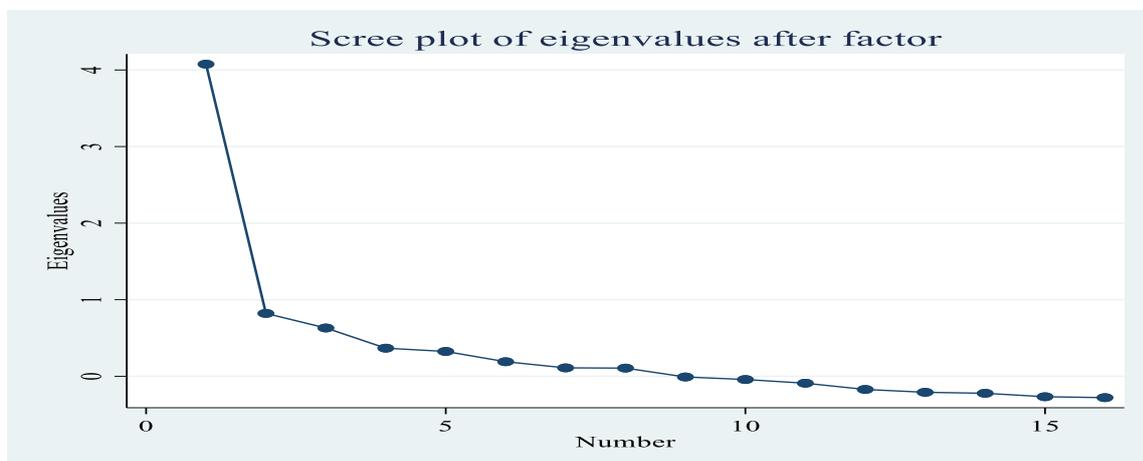
Appendix 3A: Distribution of farmers' scores and odd-Ratio of practices

Appendix 3B: Initial output from Factor analysis of OFPs to determine attitude dimension

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	4.07616	3.25517	0.7642	0.7642
Factor2	0.82098	0.19036	0.1539	0.9181
Factor3	0.63062	0.26369	0.1182	1.0364
Factor4	0.36693	0.04282	0.0688	1.1052
Factor5	0.32411	0.13395	0.0608	1.1659
Factor6	0.19016	0.08028	0.0357	1.2016
Factor7	0.10988	0.00329	0.0206	1.2222
Factor8	0.10659	0.11596	0.0200	1.2422
Factor9	-0.00937	0.03293	-0.0018	1.2404
Factor10	-0.04230	0.04829	-0.0079	1.2325
Factor11	-0.09059	0.08130	-0.0170	1.2155
Factor12	-0.17189	0.03729	-0.0322	1.1833
Factor13	-0.20919	0.01297	-0.0392	1.1441
Factor14	-0.22215	0.04512	-0.0417	1.1024
Factor15	-0.26727	0.01165	-0.0501	1.0523
Factor16	-0.27891	.	-0.0523	1

LR test: independent vs. saturated: chi2(120) = 1020.23 Prob>chi2 = 0.0000

Appendix 3C: Screeplot test of eigenvalues against respective factors



Chapter 4

Organic Fertilizer Adoption, Household Food Access, and Gender-based Farm Labor Use: Evidence from Northern Ghana

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Abstract

This paper examined organic fertilizer adoption and its effects on two household food security indicators and gender-based farm labor use among smallholder farmers in northern Ghana. An endogenous switching regression analysis shows that observed and unobserved farmer-background factors determine the decision to adopt organic fertilizer as well as the outcomes from adoption. On average, adoption is associated with an 11% increase in per capita food consumption and a 55% reduction in food gap. Adoption is also related to an increased labor use per acre by 5.9 (90%) of female worker-days and 1.3 (9%) of male worker-days, placing nearly all (82%) of the increased labor burden on female farmhands. We recommend mitigation of factors that hinder farmers from adopting the input and provision of female-user-friendly labor-saving devices for organic fertilizer use tasks.

Key words: endogenous switching regression; food access; labor use; Northern Ghana; organic fertilizer; smallholder farmers

JEL Classifications: O33, Q12, Q16

4.1 Introduction

Food insecurity will persist in Sub-Saharan Africa (SSA) unless the current decline in agricultural productivity, caused mainly by soil degradation, is halted and reversed (AfDB, 2006 and Nkonya *et al.*, 2015). Soil erosion and related factors, including soil nutrient mining, loss of organic matter and declining biodiversity, are responsible for increasing crop productivity gaps in the region (Kassie *et al.*, 2013; FAO, 2015; and Martey, 2018). Erosion has affected more than 22% of the arable lands in many countries, particularly in West Africa, jeopardizing the livelihoods of over 65% of national populations dependent on agriculture (FOA, 2015 and Nkonya *et al.*, 2015). Yet, the farm-household population in the region is rapidly growing (FAO, 2015). This limits land availability and renders traditional soil maintenance practices, like fallowing land to restore nutrients, impracticable (Pandey *et al.*, 2002). Yet, the resource-poor farmers in the region lack access to and apply mineral fertilizer at a rate far below world standard (AfDB, 2006; Sheahan *et al.*, 2017; and Ayalew *et al.*, 2020), though recent evidence of increasing fertilizer use in some countries, particularly for cereal production (Liverpool-Tasie *et al.*, 2017). This implies that the majority of farmers intensify cropping under negative nutrient balances (Martey, 2018).

In Ghana, farmers in the northeastern part of the country are most affected by soil degradation. The area lies within the Sudan and part of the Guinea Savannah zones, where a larger proportion of the landmass is hilly and rocky, having little vegetation cover (Government of Ghana, 2015). Continual removal of the scanty vegetation cover through cultivation and annual bush fires accelerate the loss of soil organic matter and useful biodiversity (Tittonell and Giller, 2013). The area also experiences the most erratic rainfall country-wide (Amikuzuno and Donkor, 2012; Wiredu, 2015; and Issahaku *et al.*, 2016).

Cereals (maize, millet, and sorghum) are the main staple crops in the area. Production of these crops constitutes the primary livelihood of the subsistence rural households (Government of Ghana, 2015). The farmer-population of this area is dense; hence, the limited land has been put under traditional exploitative cultivation practices without sufficient soil nutrient replacement (Atakora *et al.*, 2014; Danquah *et al.*, 2019 and Owusu *et al.*, 2020). Consequently, the yields of main crops continue to decline; thus, trapping many of the farm households in poverty (Atakoral *et al.*, 2014) and food insecurity cycle (Government of Ghana, 2015).

Nearly all mineral fertilizer used in the area goes into cereal crop production. The application rate in the area is usually higher than the national average (FAO, 2005) and has been increasing since the introduction of a national fertilizer subsidy program in 2008 (Wiredu, 2015). However, experts

warn of inappropriate modes of fertilizer application. They fear that the repetitive use of existing fertilizer formulations without site-specific soil test recommendations further deteriorates soil health (Atakora *et al.*, 2014; and Ayalew *et al.*, 2020). Therefore, soils are becoming increasingly non-responsive to mineral fertilizers (Atakora *et al.*, 2014). Under such a condition, the farmers do not fully benefit from their investment in any high-value external input without first rehabilitating the soils (Tittonell and Giller, 2013).

Meanwhile, ecological intensification (EI)⁵ is a win-win approach to addressing soil degradation and simultaneously improving food security (Kassie *et al.*, 2013; Kassie *et al.*, 2015; Teklewold *et al.*, 2013; and Zeweld *et al.*, 2017). EI relies on locally available organic options for maintaining ecological competitiveness and the economic viability of agriculture. Thus, it allows reduced use of inputs that could be harmful to the environment (Zeweld *et al.*, 2017). EI practices help improve soil health and enhance returns from investment in mineral fertilizer and other external inputs (Kousar and Abdulai, 2015; and Zeweld *et al.*, 2017).

Therefore, farmers within the affected area are being encouraged to adopt EI practices, mainly organic fertilizer application to resuscitate degraded soils for sustainable cropping and increased return-on-investment in other farm inputs (Government of Ghana, 2015 and Zeweld *et al.*, 2017). Organic fertilizers (O.F)⁶ use plays crucial roles in sustaining soil ecology (Tittonell and Giller, 2013). It maintains organic matter content at levels necessary for conserving soil moisture, plant nutrients and other properties required for healthy plant growth (Kassam *et al.*, 2017; Zeweld *et al.*, 2017; and Abebe and Debebe, 2019).

In terms of economics, the literature (e.g., Kassie *et al.*, 2009; Zerihun and Haile, 2017; Abebe and Debebe, 2019; and Usman *et al.*, 2015) also provides ample evidence of positive effects O.F has on crop productivity and farmer-welfare. Gelgo *et al.* (2016) reported increased incomes of farmers adopting the input in Shashemene district of Ethiopia. In Ghana, Martey (2018) found that O.F adoption improves crop productivity, incomes and poverty, but reduces total and per capita food expenditure among farm households.

⁵ Crop production is environmentally nondegrading, resource conserving, socially acceptable, technically appropriate and economically viable (FAO, 1995 as quoted in Adnan *et al.*, 2017). This means that EI maintains good yields and farm profits without undermining the soil resources on which crops depend.

⁶Organic fertilizers are carbon-based compounds that increase the productivity and growth quality of plants. These include crop residue, green manure and agroforestry, compost, animal manure, agro-processing by-products and excreta/sewage sludges and organic waste from urban centers.

Though the welfare indicators examined in the above studies are useful in gauging the overall household food access⁷, they do not capture the stability dimension, especially through self-provisioning capacity. Self-provisioning is a critical element of farm-households' food access because farmers primarily consume their own produce either direct from the farm or from storage. Furthermore, Martey (2018) studied observations from heterogeneous populations across different ecological zones with divergent types of organic fertilizer and related practices. Thus, the findings of the study do not reflect agroecology-specific situations, wherein practices are homogenous. Besides, we expect organic fertilizer adoption to occur at the cost of other input adjustments, especially labor (Fuglie and Bosch, 1995; Teklewold *et al.*, 2013). Potential increase in labor requirements could hinder O.F adoption and/or the application rate, thus diminish the associated benefits to farmers (Teklewold *et al.*, 2013). However, to the best of our knowledge, the extent to which O.F adoption affects farm-labor use in SSA has not been empirically examined. These shortcomings underscore the need for further, especially agroecology-specific, studies to inform micro/meso level O.F use policies adequately.

The main objective of this study is to evaluate the effects of organic fertilizer adoption on farm-household food access and labor use among rural farmers. Using observational data obtained from farmers in the northeastern part of Ghana, we adopted the potential outcome framework (see Imbens and Wooldridge, 2009) and applied the endogenous switching regression (ESR) to model organic fertilizer adoption simultaneously with 1) per capita food expenditure, 2) household food gap and 3) gender-segregated farm-labor used as outcome variables. Subsequently, we estimated the effects of organic fertilizer on these outcomes. The study analyzes for the first time the effect of organic fertilizer on food gap and labor use. It thus contributes to organic fertilizer literature for Ghana by providing firsthand empirical links between farm-labor use and household food-gap, on the one hand, and organic fertilizer adoption on the other.

The rest of the paper is structured as follows: the next section (4.2) describes the background to O.F practices in the study area. Section 4.3 discusses the study methodology, including sampling and data used, the theoretical and empirical model applied. Section 4.4 summarizes the data, presents econometric results for the ESR model and discusses the effects of organic fertilizer adoption on food expenditure, food gap, and labor use variables. Finally, section 4.5 summarizes the results and concludes with key policy suggestions.

⁷ Food access is the ability to acquire sufficient quality and quantities of food, while food stability refers to the continuous availability of food under all conditions (FAO, 2008).

4.2 Organic Fertilizer Use in Northeastern Ghana

The types of O.F available to farmers and the potential to improve soil; hence, farm productivity depend significantly on an area's agroecology and population dynamics (Tittonell and Giller, 2013). Organic practices like agroforestry and green manuring are almost infeasible because arable land is scarce in Northeastern Ghana and agriculture depends entirely on a rainy season too short to grow green manure before cultivating main crops. Thus, the common O.F practices among farmers in the area include crop residue restitution, composting, and the use of livestock manures (Martey, 2018). Yet, competing uses for crop residues (e.g., for feeding livestock, as fuel, or for house construction) limit its availability for use as the primary biomass in maintaining the required level of organic matter (Wekesah *et al.*, 2019). Crop-livestock integration is traditional in the area, and farmers thus have some path-dependencies in using animal manures. However, the livestock densities and the carrying capacity of local grasslands in the region cannot support the rate of manure turnover needed to supply more than one-third of household crop fields (Bationo *et al.*, 2001; Tittonell and Giller, 2013).

Nonetheless, farmers are aware of the good returns on investment in organic fertilizers and thus are motivated to increase their use (Powell and Williams, 1995; Nkonya *et al.*, 2015). As soil and weather change, the farmers must continue adapting their traditional practices to prevailing agroecological conditions to sustain quantities of organic matter they require for use (Fairhurst, 2012; and Tittonell and Giller, 2013).

The Ministry of Agriculture (MoFA) and other development agents (e.g., PAS, AGRA, NRGF, ACIDI/VOCA, OIC and GIZ)⁸ have been sensitizing smallholder farmers towards adaptation and building their capacity to source and use organic fertilizers. Capacity-building efforts have focused mainly on developing skills for enhanced collection of agro-process and domestic waste, harnessing livestock manure and crop residues, and compost preparation using these materials (Bellwood-Howard, 2013). Farmers have also been educated on the safe use of human excreta/sewage, where it is accessible (Cofie *et al.*, 2005 and 2010). Particularly, PAS and OIC have trained farmers on pit and heap methods of compost preparation and supported some farmer-groups to acquire equipment like donkey carts for gathering materials (Bellwood-Howard, 2013). ACIDI/VOCA, NRGF and AGRA have also primed farmers on efficient and effective ways of

⁸ The full names of the organizations are: PAS-Presbyterian Agriculture Station; AGRA-Alliance for Green Revolution in Africa; NRGF-Northern Rural Growth Project; ACIDI/VOCA-Agricultural Cooperative Development International/Volunteers in Overseas Cooperative Assistance; Opportunity for Industrialization Center and GIZ-Gesellschaft für Internationale Zusammenarbeit, respectively.

applying the input, including the zai-pit method and micro-dosing organic field with mineral fertilizers after germination, regardless of the quantity of organic fertilizer applied. Through such capacity-building programs, farmers now prioritize using their scarce organic amendments for staple cereals as the most important food security crops (Martey 2018). They have also adopted intercropping and rotation of cereals with legumes and learned to augment organic fertilizers with significant quantities of mineral fertilizer, especially NKP (Martey *et al.*, 2014; Chapoto *et al.*, 2015). This study drew farmers from PAS and MoFA project areas to examine the effects of organic fertilizer adoption on food security and farm labor use.

4.3 Methodology

4.3.1 Sampling, Data and Measurements

The data for this study was obtained through a recent farm-household survey we conducted, in partnership with PAS, in the North East and Upper East Regions of Ghana. As stated earlier, PAS, AGRA and NRGP through MoFA have, under different projects at various locations within the area, primed farmers towards using organic fertilizers to sustain their soil health. Except for the Bunkpurugu area, we followed PAS operational areas to sample the study participants. Prior to sampling, a discussion was held with MoFA (Bunkpurugu area) and PAS extension agents to identify the types of organic fertilizer and related practices farmers currently use.

We selected 504 households across 52 communities clustered around three PAS and one MoFA extension zones through a multi-stage cross-sectional sampling approach. At the first stage, we purposively selected PAS and MoFA extension zones to ensure equal chances of including farmers using different organic fertilizer types in the sample. PAS and MoFA extension agents in the selected zones provided lists of farming communities from which we randomly drew 30% of the communities to represent each zone. At the community level, farmer-group and opinion leaders helped to identify and compile lists of organic fertilizer adopter and non-adopter households. Households were randomly selected from the lists to represent each sub-sample group. Farmers who applied at least 1ton/acre of biomass (e.g., crop residue, animal manure, compost, domestic/urban waste, agro by-products, excreta slurry, or a combination of these) constituted the organic fertilizer user-group (adopters).

The data was collected during a face-to-face personal interview (PI) with participant farmers. Appendix 4A shows the number of communities and households sampled across the study locations. Since the study focuses on evaluating the effects of O.F. on food access and labor use, the questionnaire elicited data on food access and labor used as outcomes variables of O.F.

adoption and farmer-characteristics. For food access, we considered two critical indicators in a farm-household setting: per capita food expenditure and food stability through self-provision (indicated by food gap). Per-capita food expenditure was measured in adult equivalent units (AEU) of Ghana cedis, while food gap was captured as the duration (in months) of time a household had difficulties securing sufficient foodstuff. We used the adult equivalent units for per capita food expenditure because it is more directly linked to producer-consumer household food access and less prone to measurement errors than household income-based indicators (Tambo *et al.*, 2017). Following Tambo *et al.* (2017) and Martey (2018), our questionnaire used a 7-day recall period to identify food items consumed and thus captured the corresponding components of expenditure. We valued non-purchased food items at current market prices. Regarding labor use, farmers reported the number of worker-days used per acre during the crop season. This was further segregated into male and female worker-days⁹ in order to examine gender-based effects of O.F adoption on labor.

The survey also captured data on six categories of farmer/farming background factors (explanatory variables). Strands of literature generally on technology adoption (e.g., Fuglei and Bosch, 1995; Di Falco *et al.*, 2011; Teklewold *et al.*, 2013; Khonje *et al.*, 2014; Sheferaw *et al.*, 2014 and Tambo and Wünsch, 2017) and specifically on organic fertilizer adoption (e.g., Waithaka *et al.*, 2007; Ullah *et al.*, 2015; Chen *et al.*, 2018; Martey, 2018; and Kamau *et al.*, 2018) motivated the inclusion of these variables. The moderator variable categories are farmer/household characteristics, resource constraints, and plot-specific factors. Other groups include social capital, governance and institutional variables, information access factors, and environmental shocks. These have empirically proven to influence farmers' decision to adopt farm technology (Sheferaw *et al.*, 2009; Teklewold *et al.*, 2013; and Ayalew *et al.*, 2020). Table 4.1 shows the description and summary statistics, including the mean difference between adopters and non-adopters, for all variables used in the study.

4.3.2 *Theoretical model and estimation strategy*

Farm households aim at maximizing welfare derived from the farm-enterprise under optimal application of inputs. They take into account the net benefits of O.F when making their decision to adopt or not. We assume further that farmers are risk-neutral, and their decision to adopt or otherwise depends only on whichever gives them the maximum expected net benefit. The decision task then is to choose the option that maximizes their welfare, subject to household resource

⁹ A worker-day is equivalent to 8 hours of farm work time of man or woman's

endowment constraints. The input used and the resultant observed welfare indicators (food expenditure and food gap) are outcomes of the binary adoption decision (Teklewold *et al.*, 2013; and Sanglestsawai *et al.*, 2015). Let Q_{ja} and Q_{jn} represent the net outcome farmer j derives from O.F adoption and non-adoption, respectively. The farmer adopts O.F if $Q_{ja} > Q_{jn}$ (i.e., the net benefit from adopting exceeds that from non-adoption).

To specify the adoption model, also let U_j^* be a latent decision criterion variable (the difference between Q_{ja} and Q_{jn}) on which farmer j bases his/her decision. Further, let D_j indicates the observed binary decision such that $U_j^* = Q_{ja} - Q_{jn} > 0$ when $D_j = 1$ (i.e. if farmer j adopts O.F) and $Q_{ja} - Q_{jn} \leq 0$ when $D_j = 0$ (i.e. when farmer j does not adopt O.F). By expressing U_j^* as a function of observed farmer characteristics, denoted Z , we obtain a latent variable adoption (selection) equation that sorts farmers into adopters and non-adopter as (Di Falco *et al.*, 2011):

$$U_j^* = \gamma'Z_j + \varepsilon_j \text{ with } D_j = \begin{cases} 1 & \text{if } U_j^* > 0 \\ 0 & \text{otherwise} \end{cases} \quad , \quad (1)$$

where Z_j is a vector of household characteristics and farm attributes; γ is a vector of parameters to be estimated, while ε_j is a random term with mean zero and variance σ_ε^2 , capturing measurement errors and the effects of unobserved factors (Abdulai, 2016). Even though we cannot observe U_j^* , it can be indexed by farmer j 's observed decision D_j , such that the probability of adoption is specified as

$$\Pr(D = 1) = \Pr(U_j^* > 0) = \Pr(\varepsilon_j > -\gamma'Z_j) = 1 - F(-\gamma'Z_j) = D_j = \gamma'Z_j + \varepsilon_j \quad , \quad (2)$$

where F is the cumulative distribution function for ε . Since D_j is binary, the adoption equation (2) can be estimated consistently by a standard probit model. We can assess the effect of adoption on any of the outcome variables (Q_j) by regressing Q_j on the binary adoption decision, D_j , and other explanatory variables as below (Tambo and Wünscher, 2017);

$$Q_j = \mathbf{X}'_j\beta + \omega D_j + \mu_j \quad , \quad (3)$$

where \mathbf{X}_j is a vector of household/farm characteristics, such as age, gender, educational attainment of the household head, household size, resource endowment, social network, geographical location and inputs; ω measures the effect of organic fertilizer adoption on outcome Q_j ; μ captures measurement errors and effects of unobserved factors, with j indexing individual farmers (Abdulai and Huffman, 2014, and Tambo and Wünscher, 2017).

Equation (3) could be estimated by standard regression techniques such as ordinary least squares (OLS) if assignment to O.F adoption were random. In our observational case, however, adoption

was randomly assigned. Adopters self-selected, probably because their personal characteristics, such as innate managerial or technical ability, influence both the decision to adopt and the outcomes such that they are also the ones with high outcomes even if they do not adopt (Fuglie and Bosch 1995). It means that adopters are systematically different from non-adopters. Such systematic differences obscure the true effect of organic fertilizer adoption if obtained by equation (3) (Tambo and Wünscher, 2017). For this cross-sectional evaluation, where outcomes lack counterfactual information, we could employ either propensity score matching (PSM) or endogenous switching regression (ESR) to capture such bias (Abdulai and Huffman, 2014). However, because we also wish to identify factors driving O.F adoption by farmers, we have to apply the ESR since estimates of the probit model after PSM cannot be interpreted as coefficients of determination (Abdulai and Huffman, 2014 and Abdulai, 2016).

4.3.3 Empirical specification of the endogenous switching regression model

In the ESR framework, equation (2) sorts farmers into adopters and non-adopters, having different outcome regimes. Because we observed either Q_{ja} or Q_{jn} for every farmer, there is no counterfactual information on the outcome. Thus, the ESR approach specified potential outcome equations conditional on the adoption decision D_j as:

$$Q_{ja} = \mathbf{X}'_{ja}\beta_a + u_{ja} \quad \text{if } D_j = 1 \quad (4a)$$

$$Q_{jn} = \mathbf{X}'_{jn}\beta_n + u_{jn} \quad \text{if } D_j = 0 \quad (4b)$$

With a continuous outcome variable Q , linear regressions could be applied to estimate β_a and β_n . However, OLS estimators will give biased β s if the error terms ε_j of equation (2) correlates with those (u_{ja} and u_{jn}) of the outcome equations. In other words, there is selectivity bias to be addressed. This is done by including selectivity correction terms in the outcome equations to capture the bias (Lokshin and Sajaia, 2004; Abdulai and Huffman, 2014; Shiferaw *et al.*, 2014; Khonje *et al.*, 2015; and Tambo and Wünscher, 2017).

Error-terms u_{ja} and u_{jn} being correlated with ε_j , implies that the expected values of u_{ja} and u_{jn} , conditional on the sample selection, are not zeros. But we can assume that ε_j has a variance of $\sigma_{\varepsilon_j}^2 = 1$, and the correlation coefficients between u_j s and ε_j sum up to zero, meaning that they have a trivariate normal distribution with a zero-mean vector and variance-covariance matrix (Σ) as defined (Khonje *et al.*, 2014):

$$\begin{bmatrix} \sigma_{\varepsilon_j}^2 & \sigma_{u_{ja}\varepsilon_j} & \sigma_{u_{jn}\varepsilon_j} \\ \sigma_{\varepsilon_j u_{ja}} & \sigma_{\mu_{ja}}^2 & \cdot \\ \sigma_{\varepsilon_j u_{jn}} & \cdot & \sigma_{u_{jn}}^2 \end{bmatrix},$$

where $\sigma_{u_{ja}}^2 = \text{var}(u_{ja})$, $\sigma_{u_{jn}}^2 = \text{var}(u_{jn})$, $\sigma_{u_{ja}\varepsilon_j} = \text{cov}(u_{ja}, \varepsilon_j)$ and $\sigma_{u_{jn}\varepsilon_j} = \text{cov}(u_{jn}, \varepsilon_j)$. The $\text{cov}(u_{ja}, u_{jn})$ is undefined since we cannot observe Q_{ja} and Q_{jn} simultaneously from any farmer (Maddalla, 1983). The expected values of u_{ja} ($E(u_{ja} | D_j = 1)$) and u_{jn} ($E(u_{jn} | D_j = 0)$) contain the selection bias and are statistically equivalent to the product of the error covariances ($\sigma_{u_{ja}\varepsilon_j}$ and $\sigma_{u_{jn}\varepsilon_j}$) above and inverse Mills ratios (IMRs) computed from probabilities obtained from (2) at $\gamma'Z_j$. Thus, we calculate the IMRs (λ_{ja} and λ_{jn}) given as

$$\begin{aligned} \lambda_{ja} &= \frac{\phi(\gamma'Z_j)}{\Phi(\gamma'Z_j)}, \text{ if } D_j = 1 \\ \lambda_{jn} &= \frac{\phi(\gamma'Z_j)}{1-\Phi(\gamma'Z_j)}, \text{ if } D_j = 0 \end{aligned} \quad (5)$$

where ϕ is the standard normal probability density function, Φ is the standard normal cumulative density function of equation (2). Including λ_{ja} and λ_{jn} in the outcome equations, respectively, re-define the switching regressions that correct for selection bias as follows:

$$\begin{aligned} Q_{ja} &= \mathbf{X}_{ja}\beta_a + \sigma_{\mu_{ja}\varepsilon_j}\lambda_{ja} + \xi_{ja} \text{ if } D_j = 1 \\ Q_{jn} &= \mathbf{X}_{jn}\beta_n + \sigma_{\mu_{jn}\varepsilon_j}\lambda_{jn} + \xi_{jn} \text{ if } D_j = 0 \end{aligned} \quad (6)$$

where $\sigma_{\mu_{ja}\varepsilon_j}$ and $\sigma_{\mu_{jn}\varepsilon_j}$ become coefficients of the selection control terms λ_{ja} and λ_{jn} , capturing effects of unobserved selection variables on outcomes. ξ_{ja} and ξ_{jn} become the standard error terms with zero expectations and unit variance. Equation (6) is more consistent and efficient if estimated simultaneously with the adoption equation (2), using the full information maximum likelihood (FIML)¹⁰ estimator rather than Maddalla's (1983) two-step approach (Lokshin and Sajaia, 2004; and Tambo and Wünscher, 2017).

The FIML ESR model is identified through non-linearity of λ_{ja} and λ_{jn} (Lokshin and Sajaia, 2004), but identification is better when, at least, one variable (exclusion variable) directly affecting the adoption decision D_j but not the outcomes is included in equation (2) (Tambo and Wünscher, 2017). Following Di Falco *et al.* (2011); and Tambo and Wünscher (2017), we conducted falsification tests (see Appendix 4C)¹¹ of several potential instrumental variables against the outcome variables to identify relevant exclusion variables. The tests revealed that a household's distance to the nearest agricultural extension office is the only valid instrument for use in our case.

¹⁰ The FIML estimation is implemented in STATA using the **movestay** command by Lokshin and Sajaia (2004), which implements simultaneous estimation of the first and second stage equations.

¹¹ According to Di Falco *et al.* (2011), Khonje *et al.* (2015) and Tambo and Wünscher (2017) variables to be added in the selection model as instruments to improve ESR model identification are those that affect farmers' decision to adopt organic fertilizer, do not directly affect any of the outcome variables, at least among non-adopter.

After simultaneously estimating equations (2) and (6), we derived conditional expectations of the outcomes as follows:

Adopters with adoption (actual/observed outcome for adopters)

$$E(Q_{ja} | D_j = 1; \mathbf{X}) = \mathbf{X}_{ja}\boldsymbol{\beta}_a + \sigma_{\mu_{ja}\varepsilon_j}\lambda_{ja}, \quad (7a)$$

Non-adopters without adoption (actual/observed outcome for non-adopters)

$$E(Q_{jn} | D_j = 0; \mathbf{X}) = \mathbf{X}_{jn}\boldsymbol{\beta}_n + \sigma_{\mu_{jn}\varepsilon_j}\lambda_{jn}, \quad (7b)$$

Adopters had they not adopted (counterfactual outcome for adopters)

$$E(Q_{jn} | D_j = 1; \mathbf{X}) = \mathbf{X}_{ja}\boldsymbol{\beta}_n + \sigma_{\mu_{jn}\varepsilon_j}\lambda_{ja}, \quad (7c)$$

Non-adopters had they adopted (counterfactual outcome for non-adopters)

$$E(Q_{ja} | D_j = 0; \mathbf{X}) = \mathbf{X}_{jn}\boldsymbol{\beta}_a + \sigma_{\mu_{ja}\varepsilon_j}\lambda_{jn}, \quad (7d)$$

From these expectations, we calculate the average treatment effect on the treated (AAA) as;

$$\begin{aligned} \text{AAA} &= (7a)-(7c) = E(Q_{ja} | D_j = 1; \mathbf{X}) - E(Q_{jn} | D_j = 1; \mathbf{X}), \\ &= \mathbf{X}_{ja}(\beta_a - \beta_n) + \lambda_{ja}(\sigma_{\mu_{ja}\varepsilon_j} - \sigma_{\mu_{jn}\varepsilon_j}), \end{aligned} \quad (8)$$

where $\mathbf{X}_{ja}(\beta_a - \beta_n)$ captures the expected change in adopters' outcome if they have characteristics similar to non-adopters.

AAA estimates obtained from FIML are consistent but not precise if there is adoption effect-heterogeneity (Wooldridge, 2015). Therefore, we checked the robustness of the AAA estimates by comparing them with their precise but inconsistent counterparts obtained from endogenous adoption effect (**eteffect**) model, using the control function approach. Detail econometric results of the **eteffect** model are not presented in this paper but are available upon request. Further, we also analyzed farmer-level pre-adoption and adoption effect heterogeneity, following the procedure outlined by Di Falco *et al.* (2011). However, for policy purposes, it is essential to examine heterogeneity across relevant farmer groups. This could be done by estimating and comparing local average adoption effects (LAAE) within different quantiles of the outcomes (Issahaku and Abdulai, 2019), which implies discrete heterogeneity groups, yet heterogeneity could be continuous (Xie *et al.* 2012). Thus, similar to Xie *et al.*'s (2012) approach, we expressed farmer-specific adoption effect (adoption effect on adopters (AEA) and adoption effect on non-adopters (AEN)) as a function of the probability of adopting organic fertilizer. We then visualized trend of AEA and AEN by scatter plots fitted with local polynomials of degree one. (Xie *et al.*, 2012). That allows us to observe how effects heterogeneity (the gap between polynomials lines) differs across levels of probability to adopt.

4.4 Empirical results and discussion

In this section, we present descriptive statistics of the sample data, present and discuss econometric results of the O.F adoption probit model, followed by that of the ESR outcome models. Next, we present and discuss the estimated effects of organic fertilizer adoption on welfare and labor outcomes variables. We then conclude the section with a discussion on treatment effect heterogeneity.

4.4.1 Data summary statistics

Table 4.1 presents the summary statistics of the data we used in the study. Column three shows pooled sample means, while columns four to six display subsample means of adopters and non-adopters and their difference, respectively. A chi-square test of the mean differences showed significant differences between adopter and non-adopter households regarding key socio-economic variables, including gender, education, household size, and livestock size. Adopters also differ from non-adopters in information access and social leverage profiles, including extension visits, distance to the nearest input market, and membership of a farmer-based organization. Other characteristics distinguishing adopters from non-adopters are soil quality status, type of soil tillage practiced and experience of production shocks like drought and waterlogging. These differences mean that randomization during sampling could not yield a sample of participants with similar characteristics across the adoption regimes. This indicates that these characteristics and probably other unobserved factors drive self-selection onto adoption as well as outcomes.

Statistics of the outcome variables reported at the bottom of the table give an average per capita food consumption expenditure of about 598 Ghana Cedis (GHS) per annum. An average sampled household experiences about one month of foodstuff shortages, usually from late April to late May. This period seems shorter (0.74 months) for adopters than for non-adopters (1.5 months), although the difference is not statistically significant. Regarding labor use, an average sample farmer deploys a mean of 11.6 worker-days of female labor and 14.14 worker-days of male labor, totaling 25.74 worker-days per acre of maize. Organic fertilizer adopters, however, used significantly (at 1%) more labor than non-adopters.

Table 4.1: Summary statistics of variables

Variable	Description and Measurement of Variable	Mean	Adopters	Non-adopter	Mean Diff.
Explanatory Variables					
Dist. to Exten.	Distance (minutes' walk) to agric. ext. office	80.3	59.3	100.9	-41.60
Gender	Gender of the family head (1=male, 0=female)	0.8	0.8	0.7	0.1***
Age	Number of years	42.3	43.0	41.5	1.45
Education	Number of years of formal schooling	5.2	6.6	3.9	2.74***
Household size	Number of people in the household	9.4	9.9	8.9	0.94***
Female2male	Ratio of female to male adults in a household	3.1	3.2	3.1	0.05
Off-farm work	Off-farm work participation (dummy)	0.4	0.4	0.4	0.01
Means_Trans	0=no means, 1=bicycle, 2= motorbike/truck	1.2	1.2	1.2	0.04
FAssets	Value of farm assets (thousands of GHS)	5.6	6.2	5.0	1.16
Livestocksize	Tropical livestock units (Number)	3.6	5.0	2.2	2.82***
Farmland	Number of acres of farmland.	10.0	10.0	9.9	0.16
Plot size	Number of acres of maize plot	3.7	3.9	3.6	0.29
Walkdist	Distance (walking minutes) to plot	31.1	26.8	35.3	-8.48
Extension	Frequency of visit during the cropping season	0.4	0.7	0.0	0.70***
Inputmktdis	Walking distance (minutes) to inputs market	45.8	50.7	40.9	9.80***
Group member	FBO membership-1=yes, 0= no	0.4	0.7	0.1	0.63***
Mrktrelations	Number of grain-traders a farmer knows	1.4	1.5	1.2	0.22
LandTenure	Farmland tenure- dummy (1= own, 0= rented)	0.9	0.9	0.8	0.04
Peststress	Whether pests affect crops (dummy)	0.8	0.7	0.8	-0.12
Disease	Whether diseases affects crops(yes=1, no=0)	0.2	0.2	0.3	-0.14
Droughts	Whether drought affects crops (yes=1, no=0)	0.4	0.6	0.2	0.40***
Waterlogging	Water-loggage experiences (yes=1, no=0)	0.1	0.2	0.0	0.13***
Soil status	Mean of soil-quality scores (1 to 3)	2.1	2.2	2.1	0.06*
Capital exp.	Capital expenditure(in GHS) on the plot	78.4	77.2	79.6	-2.39
Herbicides	Herbicides cost (in GHS) per acre.	21.0	22.7	19.3	3.48
Tillage mode	Dummy:1=minimum tillage, 0=conventional	0.1	0.2	0.0	0.22***
Mineral fertilizer	Kilograms of mineral fertilizer used per acre	99.3	89.1	109.2	-20.10
Seedgrade	Seed quality- (1= improved seed, 0=landrace)	0.5	0.5	0.5	-0.05
Bunpk. Zone 0	Bunkpurugu extension area -dummy	0.33	0.26	0.41	-0.15
Langb. Zone 1	Langbinsi extension area- dummy	0.21	0.27	0.15	0.12***
Garuwest Zone 2	Manga-Bazua area-dummy	0.13	0.21	0.04	0.17***
Garueast _Zone 3	Garu-Tempene extension area-dummy	0.33	0.26	0.41	-0.15
Outcome Variables					
Food cons. Exp	Food consumption expenditure/adult (in GHS)	597.9	605.51	590.43	15.07
Food gap	Number of months of food supply shortages	1.16	0.74	1.56	-0.82
Female labor	Female labor used (workerdays/acre)	11.60	15.37	9.48	5.89***
Male labor	Male labor used (workerdays/acre)	14.14	16.93	11.39	5.55***
Observations		504	250	254	

Figure 4.1 shows kernel density distribution of the four outcome variables, highlighting systematic differences between adopters and non-adopters, affirming the validity of the ESR model. Since the ESR relies on a linear function of outcomes, we carried out Box-Cox's functional-form tests to identify and appropriately specify each outcome equation. The test reveals (see appendix 4B) that food consumption expenditure follows a log-linear function, while food gap follows a multiplicative inverse (**reciprocal**) function. Female labor and male labor each support a linear identity process.

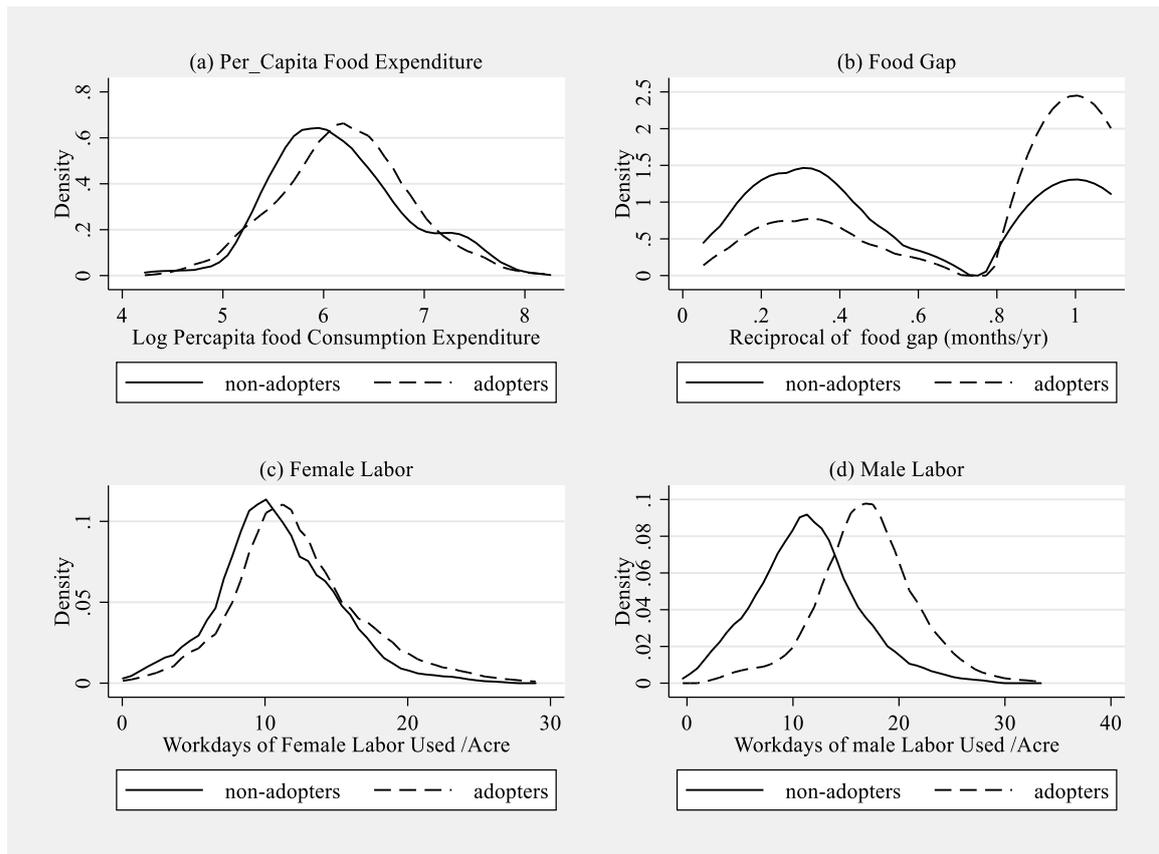


Figure 4.1: Kernel density distribution of outcome variables by adoption status

4.4.2 Determinants of organic fertilizer adoption

An initial probit model for O.F adoption mechanism showed that the explanatory variables of our model jointly determine adoption (LR $\chi^2(34) = 545.02$ [0.000], Pseudo $R^2 = 0.78$) and correctly predict about 94% of observed organic fertilizer adoption. The results for the first-stage adoption (selection) model are presented in Table 4.2. The excluded variable (i.e., distance to extension office) is statistically significant, affirming its validity as an instrument for identifying the empirical model. The coefficients of other variables remained almost the same when the model is estimated simultaneously with any outcome model. The error term of the adoption model correlates with that of food gap and female labor use equations.

O.F adoption is significantly explained by (a) household characteristics (gender, age and educational attainment of household head, household size, and female-to-male adults ratio); (b) resource endowment (tropical livestock units, cultivable farmland available, land tenure); (c) market, information and social leverage constraints (extension visit, distance to input market, farmer-group membership and market relationships) and (d) husbandry practices/plot-specific production shocks (tillage type, mineral fertilizer use, pest stress, disease occurrence, drought, and

waterlogged conditions). Finally, probability of adoption also correlates positively with a location within PAS extension clusters (zone) relative to Bunkpurugu zone.

Female-headed households are more likely to adopt organic fertilizer than male-headed ones. The age shows a quadratic relationship with the likelihood of O.F adoption. From youth, age increases the likelihood of adoption, but this relationship tends to decrease for farmers beyond their prime age, as indicated by the quadratic age term (age²). Unlike the mixed-findings by Martey (2018), education is found in this study to associate with an increased likelihood of adoption. This supports previous findings (e.g., Kassie *et al.* (2015) that better-educated farmers are able to access information required to understand farm technology; in this case, the complex relationship between soil health and organic practices and, therefore, are more likely to adopt O.F than those with less education. Household size is significant and positively, meaning that households with more members are more likely to adopt than their counterparts with fewer members. This is in line with the assertion that O.F use is labor-demanding, and households capable of meeting the requirement will, more likely, adopt the technology (Chikowo *et al.*, 2014). However, households with more female farmworkers are less likely to adopt the input's use than those having more male farmworkers.

Among the resource endowment factors, the number of tropical livestock units a farmer owns has a significant positive relationship with O.F adoption. Since organic fertilizers are not commercially available, farmers who have substantial livestock herds have better access to it, in the form of animal manure, than those without livestock. Hence, they are more likely to use organic fertilizer than those without livestock. The number of acres of arable land available to a household (farmland) seems to reduce the probability of using organic fertilizer. On the contrary, ownership (tenure) of the plot on which organic fertilizer is applied is associated with increased tendency to use organic fertilizer. Organic fertilizers release nutrients and build organic matter content of soil slowly, with resultant-yield benefits accruing in the medium to long run (Waithaka *et al.*, 2007). Only farmers on owned plots are sure to derive any such benefits themselves and are thus more motivated and likely to invest in organic fertilizer (Jacoby *et al.*, 2002; Jacoby *et al.*, 2008; Abdulai, Owusu and Goetz, 2011; Kousar *et al.*, 2016; and Chen *et al.*, 2018).

Table 4.2: First-stage FIML estimates of organic fertilizer adoption probit model
Adoption probit model, jointly estimated with:

Explanatory Variable	LogFood Consump.			
	Expenditure	Recip. Food gap	Female labor	Male labor
EXTFdistance	-0.019*** (0.003)	-0.020*** (0.002)	-0.021*** (0.002)	-0.020*** (0.001)
Gender	-0.302 (0.279)	-0.426* (0.239)	-0.487** (0.228)	-0.476 (0.296)
Age	0.098*** (0.029)	0.087* (0.053)	0.085 (0.053)	0.073 (0.047)
Age ²	-0.001*** (0.000)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.000)
Edu	0.036*** (0.012)	0.054*** (0.007)	0.042*** (0.014)	0.033** (0.014)
Household Size	0.090*** (0.026)	0.088*** (0.028)	0.084*** (0.022)	0.102*** (0.017)
F2M_Ratio	-0.018*** (0.003)	-0.017*** (0.003)	-0.020*** (0.002)	-0.018*** (0.002)
Input Market Distance	0.224 (0.142)	0.012*** (0.002)	0.011*** (0.003)	0.010*** (0.001)
FAssets	-0.075 (0.115)	-0.013 (0.008)	-0.013 (0.014)	-0.015 (0.010)
Lifestocksize (TLUs)	0.053*** (0.016)	0.055*** (0.014)	0.057*** (0.021)	0.055*** (0.021)
Farmland	-0.426*** (0.101)	-0.039* (0.021)	-0.028 (0.039)	-0.039 (0.029)
Extension	2.012*** (0.084)	1.800*** (0.201)	2.093*** (0.041)	1.943*** (0.076)
LandTenure	0.422*** (0.164)	0.370** (0.156)	0.425 (0.341)	0.470** (0.190)
Groupmember	2.223*** (0.470)	2.094*** (0.251)	2.229*** (0.379)	2.183*** (0.383)
Mrktrelations	-0.167*** (0.037)	-0.122** (0.047)	-0.201*** (0.043)	-0.183*** (0.055)
Tillage mode	1.548*** (0.516)	2.031*** (0.372)	1.961*** (0.507)	1.967*** (0.529)
Mineral fertilizer	-0.236*** (0.040)	-0.006 (0.004)	-0.005 (0.005)	-0.004 (0.005)
Langb. _Zone 1	2.399*** (0.331)	2.447*** (0.445)	2.695*** (0.300)	2.598*** (0.277)
Garuwest _Zone 2	4.682*** (0.514)	4.503*** (0.303)	5.024*** (0.399)	4.922*** (0.364)
Garueast _Zone 3	3.588*** (0.745)	3.933*** (0.504)	4.042*** (0.575)	3.959*** (0.600)
Joint sig. of plot-specific Variables. $\chi^2(3)$	9.120* [0.028]	177.76*** [0.000]	2.340* [0.505]	23.71*** [0.000]
Constant	-2.879 (1.897)	-4.806** (2.052)	-4.420** (1.960)	-4.408** (2.170)
Log pseudo LR	-384.292	-173.837	-1470.334	-1502.731
Observations	504	504	504	504

*** p<0.01, ** p<0.05, * p<0.1 and [] =p> χ^2 . Robust standard errors in parentheses. Other variables controlled for are: *meanstrans*, *plotsize*, *walkdisttoplot*, *peststress*, *disease*, *drought watrlog*, *SoilStat*, *capitalexp*, *herbvaluacre*, *seedgrade*, *off-farmincom* and *OffFarmRes*.

Of the information, market and social leverage factors, the distance between a household and a local input market, the number of extension visits, and membership of farmer-based organizations significantly increase the probability of O.F adoption. This is in line with findings of previous

studies that agricultural extension services, through information and skill enhancement, enable farmers to adopt new technologies (Abdulai and Huffman, 2014; Abdulai, 2016; and Issahaku and Abdulai, 2019). Improved access to information through interaction with extension agents and fellow farmers increases awareness of the need to use organic soil amendments; hence, the probability of adoption. Distance to the nearest input market has a similar relationship with O.F use, probably because it limits access to the commercial alternatives (i.e., mineral fertilizers); thus, inducing farmers to adopt organic fertilizers, which can be sourced locally. However, the number of trusted market relations (traders) negatively correlates with the likelihood of adoption. Access to traders seems to enhance farmers' capacity to access and use mineral fertilizers (Teklewold *et al.*, 2013). Hence, it is reasonable to assert that organic fertilizer is a traditional resource-poor soil management input rather than a modern technology to sample farmers.

Regarding husbandry practices, minimum tillage is related to an increased probability of using organic fertilizer. That is because farmers in the area generally do not practice minimum tillage, except when they need to apply organic fertilizer by the Zai pit method. On the contrary, the quantity of mineral fertilizer a farmer applies tends to relate to a reduced likelihood of O.F adoption, indicating farmers' perceived substitutability of the inputs (Bellwood-Howard and Alhassan, 2016). Previous experience of production shocks such as droughts and pest-stress encourages adoption, while crop disease incidence seems to discourage adoption, though statistically not very significant. This result is consistent with Teklewold *et al.*'s (2013) findings related to adopting sustainable agricultural practices in Ethiopia.

Lastly, the location of a farm household, relative to those found within extension zone 0 (Bunkp., reference zone), significantly determines organic fertilizer adoption. Households in zone 1 (Langbinsi area), zone 3 (Garu-Tempane area) and zone 2 (Manga-Basua area) are more likely to use organic fertilizer than their counterparts in Bunkpurugu zone. This could be attributed to better access to extension and organic fertilizer interventions through PAS and its affiliates.

4.4.3 *Factors explaining household food expenditure, food gap and labor use*

Table 4.3 presents the results of the second-stage ESR outcome model for adopters and non-adopters, respectively. At the bottom of the table are correlation coefficients ($\rho_{ja\epsilon}$ and $\rho_{jn\epsilon}$) between error terms of the adoption equation and that of the outcome regime equations. Statistically, a significant value for these coefficients indicates considerable self-selection of farmers into the regimes based on unobserved factors, influencing both adoption decisions and outcomes. That could bias our estimates of the effects of O.F use had it not been accounted for (Tambo and

Wünscher, 2017). The ρ_{jne} in the non-adopter regimes and the Wald test of independence of equations are statistically significant. We thus had to control for selection bias by applying ESR in order to obtain accurate estimates of O.F adoption effects on food gap and female labor. A positive ρ_{jne} (in the non-adopter regime) between food gap and the adoption model suggests that non-adopters' decision not to adopt leads to a reduced food gap. By contrast, the negative ρ_{jne} between the female labor use and adoption equations indicates increased female labor use under non-adoption.

Similar biases may exist in the other outcome (logFCE and male labor) equations but have not been detected, probably due to low statistical power. Hence, the empirical relevance of using the ESR approach in this study (Issahaku and Abdulai, 2019), even though the insignificant ρ_{jae} s mean that adopters do no better or worse than a farmer selected at random. The transformed error covariances, $\ln\sigma_{jae}$, and $\ln\sigma_{jne}$, also reported at the bottom, are highly significant, implying endogenous switching of outcomes between adoption and non-adoption (Tambo and Wünscher, 2017). The coefficients having the same sign, in this case, imply that farmers' decision to adopt organic fertilizer is not based on any comparative advantage of organic fertilizer; rather, they choose a fertilizer regime that makes them better off.

The estimates in Table 4.3 show that gender, age, and education of household heads do not affect food consumption expenditure (LogFCE) and food gap (FG) but negatively influence labor used, especially female labor. Household size is negatively related to logFCE of both regimes and to FG of the non-adopter regime but positively associated with female labor use by adopters. This means that large households generally have low FCE, while only non-adopter large households have a high FG compared to their smaller counterparts. Large adopter households use more female labor than smaller households, probably because they have more household labor available. Similarly, a higher female-to-male ratio in a household is associated with an extended food-gap period and more female labor use than their fellow adopters. Farm asset value is also significant and positively affects FCE, FG, and female labor among non-adopters but negatively relates to adopters' female labor use. Tropical livestock size (TLU) relates to only labor use with opposing effects in adopters and non-adopters. The size of total arable land a household possesses has similar relationship with outcomes of adopters and non-adopters. However, the relationship with FCE of adopters, FG of non-adopters, and male labor use for both regimes are not statistically significant.

Table 4.3: ESR estimates of determinants of household food access and labor used

VARIABLE	Log Food Cons. expenditure		Recip. Food Gap		Female labor		Male labor	
	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Gender	-0.010 (0.125)	0.050 (0.041)	0.016 (0.033)	0.038 (0.076)	-0.071 (0.473)	-1.338* (0.800)	-1.532*** (0.484)	-0.256** (0.111)
Age	0.001 (0.004)	0.014 (0.012)	-0.001 (0.009)	-0.001 (0.003)	0.235*** (0.047)	0.177** (0.078)	-0.217 (0.135)	0.088 (0.096)
Age2	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.002*** (0.000)	-0.002** (0.001)	0.002* (0.001)	-0.001 (0.001)
Edu	0.009* (0.005)	0.006 (0.004)	0.001 (0.003)	0.002 (0.008)	0.105* (0.063)	-0.031 (0.046)	0.073 (0.074)	0.172** (0.079)
Household size	-0.039*** (0.006)	-0.090*** (0.014)	0.007 (0.010)	-0.004*** (0.000)	0.033*** (0.013)	-0.036 (0.091)	0.108 (0.115)	0.079 (0.160)
F2M_ratio	0.001 (0.001)	0.000 (0.000)	-0.002*** (0.000)	-0.001 (0.000)	-0.009*** (0.003)	-0.001 (0.002)	0.007 (0.006)	-0.007 (0.006)
Input market dist.	0.012 (0.032)	-0.041*** (0.014)	-0.001 (0.000)	-0.001 (0.001)	0.018*** (0.005)	-0.014 (0.013)	0.016 (0.015)	-0.002 (0.011)
FAssets	0.039 (0.029)	0.055*** (0.010)	0.000 (0.002)	0.004*** (0.001)	-0.037* (0.021)	0.078*** (0.022)	-0.013 (0.026)	0.006 (0.030)
Livestock(TLUs)	0.004 (0.002)	-0.001 (0.004)	-0.000 (0.001)	-0.006 (0.007)	0.053*** (0.005)	-0.068** (0.029)	-0.034*** (0.011)	0.200*** (0.059)
Farmland	-0.014 (0.095)	0.074* (0.045)	-0.005** (0.002)	0.001 (0.008)	0.121*** (0.031)	-0.075* (0.041)	0.072 (0.050)	-0.034 (0.068)
Extension	-0.032 (0.030)	-0.548*** (0.057)	0.029 (0.023)	0.330*** (0.023)	0.082 (0.466)	-0.927*** (0.180)	-1.017** (0.434)	2.684*** (0.821)
LandTenure	0.071 (0.123)	-0.123*** (0.033)	0.022 (0.044)	0.093 (0.061)	-1.210* (0.652)	-0.622 (0.696)	-0.727 (0.461)	0.223 (0.826)
Tillage mode	0.240** (0.097)	-0.026 (0.053)	-0.020 (0.048)	0.999*** (0.115)	-1.139 (0.898)	-2.218 (1.679)	0.724 (0.635)	3.444** (1.681)
Mineral fert	-0.007 (0.013)	0.016 (0.012)	-0.000 (0.001)	0.000 (0.000)	0.006 (0.009)	0.019*** (0.005)	0.002 (0.009)	0.001 (0.006)
Groupmember	0.081** (0.035)	-0.006 (0.157)	0.162 (0.103)	0.207* (0.107)	0.101 (1.944)	-1.760*** (0.682)	-1.142 (1.076)	-0.722 (0.982)
Mrktrelations	0.041 (0.025)	-0.069*** (0.025)	-0.028 (0.029)	-0.017** (0.008)	-0.014 (0.205)	0.389*** (0.081)	0.393*** (0.094)	0.550 (0.343)
Langb. Zone 1	0.117*** (0.030)	-0.344*** (0.112)	-0.153* (0.088)	0.020 (0.086)	1.455* (0.783)	0.230 (0.391)	0.647 (0.813)	2.365*** (0.762)
Garuwest Zone 2	0.267* (0.138)	-0.683*** (0.117)	-0.124 (0.082)	-0.371*** (0.143)	1.296** (0.551)	-1.636* (0.892)	0.016 (1.963)	4.669*** (0.955)
Garueast Zone 3	0.050 (0.118)	-0.218 (0.142)	-0.249*** (0.085)	0.177** (0.073)	2.535*** (0.485)	-2.502*** (0.333)	1.370 (1.551)	2.708*** (0.738)
Joint sig.(plot vars) $\chi^2(37)$	69.24*** [0.001]	72.40*** [0.000]	71.12*** [0.000]	72.81*** [0.000]	65.17*** [0.003]	66.96 *** [0.002]	64.20*** [0.004]	63.17** [0.005]
$\ln\sigma_{j\alpha\epsilon}/\ln\sigma_{j\eta\epsilon}$	-0.737*** (0.133)	-0.863*** (0.123)	-1.266*** (0.295)	-1.151*** (0.089)	1.408*** (0.015)	1.302*** (0.021)	1.404*** (0.006)	1.424*** (0.022)
$\rho_{j\alpha\epsilon}/\rho_{j\eta\epsilon}$	0.139 (0.127)	0.128 (0.378)	0.545 (0.577)	0.511* (0.294)	0.013 (0.723)	-0.485* (0.278)	-0.176 (0.415)	0.280 (0.470)
Wald test of indep. ($\rho = 0$)	0.61 [0.4363]		6.90*** [0.008]		3.72* [0.053]		1.32 [0.250]	
Constant	6.023*** (0.263)	6.090*** (0.216)	0.731*** (0.151)	0.392 (0.241)	6.909 (4.424)	9.700*** (1.411)	20.347*** (1.461)	0.830 (2.065)
Observations	250	254	250	254	250	254	250	254

*** p<0.01, ** p<0.05, * p<0.1 Robust standard errors in parentheses. Other variables included are: meanstrans, plot size, walkdisttoplot, disease, Drought, watrlogg, SoilStat, capitalex herbvaluacre, seedgrade, peststress, OffFarmRes, and offfarmincom. For their coefficients and sig. level, the un-edited Stata model outputs are available upon request.

Besides the above household characteristics, market and information access variables, including extension contacts, membership of farmer-group, and relationship with traders, also significantly influence various outcomes under the different adoption regimes differently. The same holds for the geographical location of households relative to Bunkpurugu area (reference zone). Lastly, we refer the reader to Table 4.3 for individual effects of plot-specific variables. Even though some of the variables have insignificant coefficients, a joint significance test result (see $\chi^2(37)$) is highly significant (at 1%). Based on equations 7a to 7d, we obtained conditional expected outcomes for each adoption regime and computed different measures of O.F adoption effects as presented and discussed below.

4.4.4 *Effects of organic fertilizer adoption on food access and farm-labor use*¹²

Table 4.4 shows expected outcomes, the average adoption effect on the treated (AAA)¹³, the average adoption effect on the untreated (AAN), and adoption effect-heterogeneity indexes (BH1, BH2, and AH) for each outcome variable (under the first column). BH1 and BH2 are transitional and base-heterogeneity, respectively, while AH indicates average effect-heterogeneity, showing whether the effect of organic fertilizer is more or less for adopters than non-adopters, in a counterfactual situation that non-adopters did adopt (Di *et al.*, 2011). In other words, AH represents the effect of selection on adopters (Wooldridge, 2015). We obtained alternative estimates for the adoption effects (see appendix 4D) using the endogenous adoption effect (**eteffects**) model to check the robustness of ESR estimates.

The eteffects-based AAA estimates have the same signs and are close to those from the ESR model, even though, except for female labor use, they are not statistically significant. The eteffects model employs the control-function estimator, which gives precise but inconsistent and less robust estimates because of sensitivity to the adoption selection bias and influential observations (Wooldridge, 2015). Thus, its estimates are subject to larger standard errors than those of ESR, where there is self-selectivity (significant $\ln\sigma_{ja\epsilon}/\ln\sigma_{jn\epsilon}$) and or effect heterogeneities (BH and AH). On the other hand, the ESR model estimated by the FIML exploits all available information

¹² We defined the average effect of adoption on adopters as average effect treatment on the treated (AAA), and the average potential effect of adoption on non-adopters as the average effect of treatment on untreated (AAN) so that we continue to used the latter set of terms, because they are well established in the literature

¹³ AAA is the average difference between the actual expected outcome of adopters (^a) and its counterfactual expected outcome (^c) had they not adopted. Similarly, AAN is the difference between (^d), the counterfactual expected outcome of non-adopters had they adopted, and the actual expected outcome (^b). BH1, BH2 and AH are (a)-(d), c-b and AAA-AAN, respectively.

in the data to fit the model. Hence, the estimates are more consistent than those of the control function estimator (Issahaku and Abdulai, 2019).

Table 4.4. ESR-based average expected outcomes; treatment and heterogeneity effects

Outcome variable	Subsample	Expected outcomes		Adoption (Adoption) Effects		
		With Adoption	Without adoption	Difference		% change
Log FCE per AE	Adopters	6.212 ^a (0.025)	5.620 ^c (0.050)	AAA	0.595*** (0.040)	11
	Non-adopters	6.033 ^d (0.027)	6.159 ^b (0.031)	AAN	-0.126*** (0.021)	
	Heterogeneity Effects	BH1=0.179*** (0.014)	BH2=-0.539*** (0.018)	AH	0.721*** (0.016)	
Food Gap	Adopters	1.231 (0.047)	0.793 (0.010)	AAA	0.438*** (0.044)	55
	Non-adopters	0.591 (0.010)	0.623 (0.008)	AAN	-0.032** (0.0126)	
	Heterogeneity Effects	BH1=0.640*** (0.015)	BH2=0.170*** (0.001)	AH	0.470*** (0.015)	
Female labor days /acre	Adopters	12.316 (0.108)	6.466 (0.159)	AAA	5.850*** (0.198)	90
	Non-adopters	11.455 (0.100)	10.893 (0.104)	AAN	0.562*** (0.152)	
	Heterogeneity Effects	BH1=0.861*** (0.029)	BH2=-4.427*** (0.032)	AH	5.288*** (0.037)	
Male labor days/acre	Adopters	16.932 (0.127)	15.605 (0.263)	AAA	1.327*** (0.320)	9
	Non-adopters	18.618 (0.117)	11.387 (0.143)	AAN	7.230*** (0.189)	
	Heterogeneity Effects	BH1=-1.686*** (0.031)	BH2=4.218*** (0.040)	AH	-5.903*** (0.037)	

Note: standard error in parenthesis. **, *** significant at 5% and 1% respectively. ^a and ^b are actual expected outcomes for adopters and non-adopter, respectively, c and d are their counterfactual outcomes. For food gap, +AAA means decrease, while the reverse is true for -AAN since the estimates are reciprocals.

Estimated average effects of adoption show that food consumption expenditure for adopter households increased by about 0.6 log units (AAA=0.595) over what it would have been, had they not adopted. This represents about 11% (GHS 30.35) increased consumption in adopter-households under O.F adoption. However, food consumption would have been 2% lower in non-adopter households (GHS 9.46) had they adopted O.F (AAN= -0.126 log units). These results, as indicated earlier, imply that adopters are better off adopting organic fertilizer, while non-adopters are also better off not adopting. However, adopters are far better off under their decision to adopt than non-adopters are under non-adoption. The base and transitional effect heterogeneity estimates (BH1, BH2 and AH) indicate that adopters and non-adopters are systematically different regarding their background characteristics. This makes adopters higher per capita food consumers than non-

adopters. This meso-level finding is at variance with the macro-level evidence by Martey (2018) that organic fertilizer adoption insignificantly lowers food consumption expenditure. The difference could be due to the present study sample consisting of more subsistence than commercially oriented farm households. For this reason, adopters' additional farm proceeds may result in higher food consumption rather than in the other household expenditures reported in Martey (2018). It could also be that the previous study's estimates were biased because of averaging over different agroecological zones, stressing the need to study the agroecology-specific situation further.

The food gap estimate gives an AAA of 0.438 reciprocal months of food gap, representing 0.69 months (55%) decrease from the mean food gap that adopter-households would have experienced, had they not adopted. Non-adopter households, on the other hand, have a reciprocal of 0.623 food gap months but would have had 0.591 had they adopted organic fertilizer. Therefore, the AAN (-0.032) represents a 5% increase in the duration of the food gap, had non-adopters adopted organic fertilizer. These results show that organic fertilizer adoption decreases food deficits in adopter households, though they still would have experienced fewer months of food inadequacy than non-adopters had they not adopted.

Regarding labor use, the AAA shows that organic fertilizer adoption results in a vast increase (5.9) in female worker-days, from 6.5/acre to 12.3/acre, representing 90%. For non-adopters, the difference between expected labor use, if they had adopted, and the actual use under non-adoption (AAN) is 0.56 worker-days, representing a 5% increase. Hence the transitional heterogeneity (AH=5.3 worker-days) indicates that the effect is more on adopters than non-adopters. This pattern is, however, reversed in the case of male labor use. The AAA on male labor used by adopters is about 9% (1.3 worker-days) more than they would have used if they had not adopted organic fertilizer. In the counterfactual case that non-adopters would have adopted, the AAN indicates that they would have used 7.2 worker-days (63%) more male labor. This means that the effect of O.F adoption on male labor use (as indicated by the negative AH) is less for adopter households than for non-adopters. In general, the results regarding labor use are consistent with Teklewold *et al.*'s (2013) findings that adopting sustainable intensification practices increases farm-labor use, with female workers supplying the extra labor needed. For O.F in particular, much human effort is necessary, in place of machinery/carting equipment, to collect, transport and apply the needed high tonnage (Xu *et al.*, 2014). Farmers in the study area generally lack access to machinery/carting equipment and thus traditionally employ young women to carry out such operations.

4.4.5 Organic fertilizer effect heterogeneity

The indexes (BH1, BH2 and AH) in Table 4 are average deviations of the adoption effects from the sample mean. They indicate the presence and general direction of pre-adoption and adoption effects heterogeneity across adopters and non-adopters. We can observe the heterogeneity trend by analyzing farmer-specific deviations from their sample means (AAA and AAN). Figure 4.2 shows scatter plots of AEA, AEN, and fitted polynomial lines of AAA (pink) and AAN (green) for each outcome variable against the probability of adopting O.F. The gap between the fitted lines indicates the transitional heterogeneity of adopters and non-adopters with equal probability to adopt at any point along the probability continuum. For per capita food consumption expenditure, adoption effect heterogeneity is high between farmers with probability ranging from 0.3 to 0.6, where the majority of non-adopters have a negative AAN. The heterogeneity between farmers with probabilities beyond 0.6 is low but positive and appears to increase for probabilities approaching 0.9. The intuition behind this is that non-adopters with an adoption probability above 0.6 will improve their per capita food consumption if they are facilitated to adopt, whereas the same cannot be said about those with low adoption probabilities.

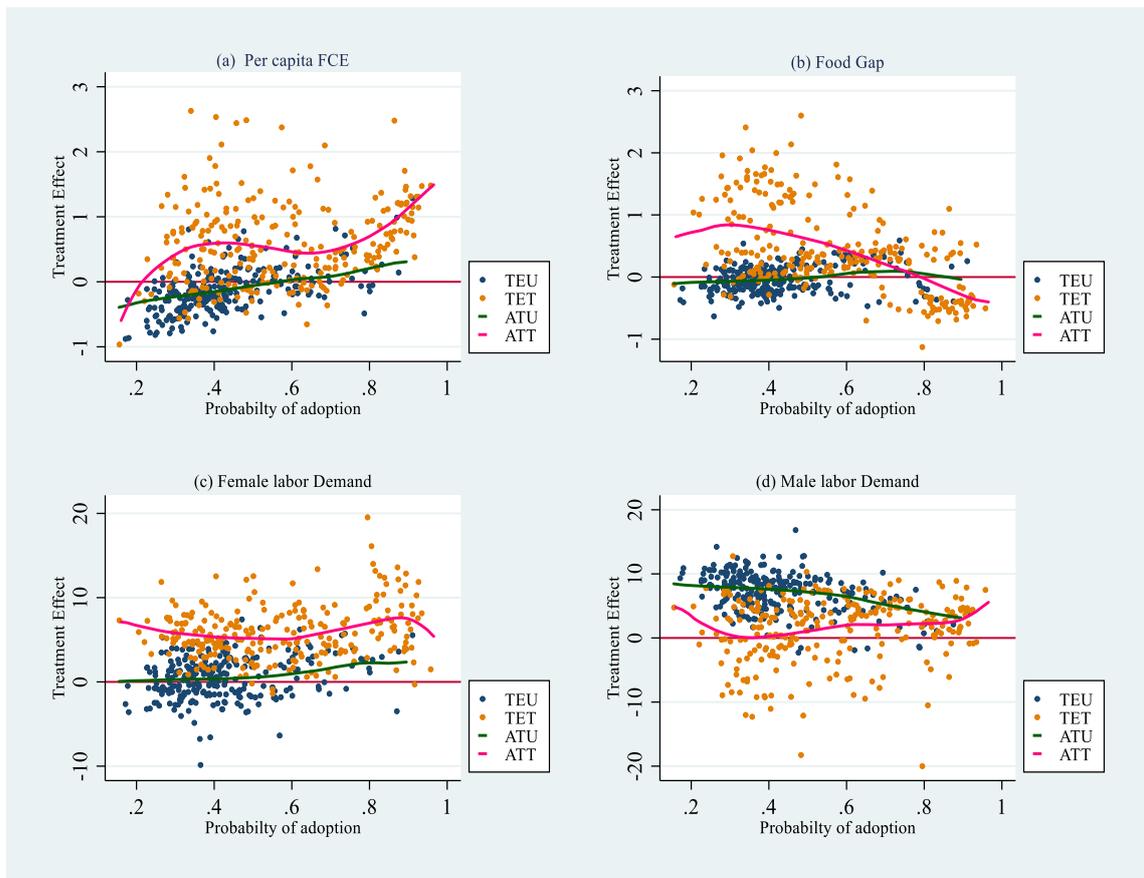


Figure 4.2. Scatter plots of treatment effects with polynomial lines by adoption status

The adoption effect on the food gap among adopters decreases from positive to negative as the probability of adoption increases, while that of non-adopters remains negative except for those with probabilities between 0.6 and 0.8. Thus, AH becomes negative beyond probabilities of 0.8, where non-adopters have almost zero but higher O.F effects than adopters. In that case, encouraging non-adopters to adopt without first changing the background conditions selecting them on non-adoption will yield no benefit. Similar to the trend observed in AH of the food gap is that of male labor use. In this case, however, the AH effect is negative at all probabilities of adoption, meaning that non-adopters, if they adopt, will use more male labor than adopters. Finally, for female labor demand, the effect of adoption is positive for both adopters and non-adopters but higher on the adopters than the non-adopters. However, the difference (AH) between the two remains relatively unchanged at all probabilities of adoption.

4.5 Summary and Conclusions

This paper used observational data obtained from 504 smallholder maize farmers in Northeastern Ghana to examine organic fertilizer adoption and its effects on farm household food access on the one hand and farm labor use on the other. Given that farmers are characteristically different and self-select onto the adoption regimes, we employed the ESR approach to account for self-selectivity bias while modeling adoption and expected outcome for each regime.

The adoption model estimates show that household characteristics, such as the age, gender, educational attainment of household head, household size, and location of household in an extension zone with PAS operations, significantly correlate with the probability of adopting organic fertilizer. Resource-based, plot-specific, and environmental factors like households' livestock size, farmland ownership, minimum tillage practice, and previous drought experience also tend farmers to adopt organic fertilizer. Social capital, governance and institutional factors supporting organic fertilizer adoption include household distance to input market, membership to farmer-group, and access to extension services. On the other hand, factors like farmland, farm capital expenses, mineral fertilizer used, the number of grain traders a household has contact with and distance to the nearest agricultural extension office negatively correlate with the probability of adoption.

These characteristics have mixed effects across adopters and non-adopters outcome equations, except education, which positively affects outcomes of both regimes. Generally, adoption is not based on any comparative advantage organic fertilizer has but instead on whichever regime gives the farmer the best outcome.

The ESR model results reveal that both the observed and some unobserved factors influence farmers' outcomes, not only through adoption but also directly. This means that our estimates for organic fertilizer effects would have been biased had we not applied the ESR model. Adoption effect-heterogeneity trend indicates that we would have underestimated the effects on food consumption expenditure, food gap, and female-labor use while overestimating that of male-labor use. The effect estimates show that organic fertilizer adoption improves household food access by significantly increasing per-capita food consumption expenditure while reducing food gap period. Unfortunately, adoption also increases labor requirement by about one-third, placing nearly all the increased labor burden on female farmhands. This means that though organic fertilizer adoption can improve food security among farm households, it could be severely hindered, especially by female-labor constraints.

From a policy perspective, these findings have implications for current and future interventions seeking increased organic fertilizer use in the country. Investment in rural education and improved access to organic soil management information through farmer-organizations and extension services are strategic measures to promote organic fertilizer adoption. For short-term measures to draw in non-adopters, unobserved factors opposing farmers' motivations to use organic fertilizer, including misconceptions about the input, need to be identified and mitigated. The negative coefficient of mineral fertilizer in the adoption process suggests that farmers wrongly perceive mineral and organic fertilizers as substitutes (Bellwood-Howard and Al-hassan, 2016). Hence, the need to sensitize farmers more on the complementary roles the inputs play in sustainable crop production. Interventions should consider providing female-user-friendly labor-saving devices for collection, transportation, and organic fertilizer application to facilitate uptake and intensification of the inputs' use in the area.

Finally, we note that, though this paper contributes to literature, empirical evidence of the link between organic fertilizer and critical farm-household welfare indicators, it relied on a cross-sectional data set. Thus, it does not account for time adjustments in organic fertilizer use and associated long-term beneficial effects on the welfare outcomes (Martey, 2018; and Chen *et al.*, 2018). Hence, the results should be interpreted with caution.

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Appendices 4

Appendix 4A: Distribution of sample households in the study area

Zone	Number of Communities	Organic fertilizer adopters	Non-organic fertilizer adopters	Total
1. Bunkpurugu	14	82	85	167
2. Garu East	13	76	89	153
3. Langbinsi	13	56	50	106
4. Garu West	12	36	30	66
Study area	52	250	254	504

Appendix 4B: Box-cox model specification test

Food Consumption exp. (log-log specifications)				
Test	Transformation power	Restricted	LR statistic	P-value
H0:		log likelihood	chi2	Prob > chi2
lambda =	-1	-3682.33	328.9	0
lambda =	0	-3518.21	0.66	0.415
lambda =	1	-3713.7	391.64	0
Food gap (multiplicative inverse = -1)				
H0:		log likelihood	chi2	Prob > chi2
theta =	-1	-682.60184	1.49	0.223
theta =	0	-720.47986	77.24	0
theta =	1	-877.2924	390.87	0
Labor (linear)				
H0:		log likelihood	chi2	Prob > chi2
lambda =	-1	-1939.9069	904.48	0
lambda =	0	-1563.2747	151.22	0
lambda =	1	-1488.7859	2.24	0.134

Appendix 4C: Falsification test for exclusion variable (distance to extension office)

Exclusion Variable	Outcome Variable			
	Food consumption expenditure	Food gap	Female labor	Male labor
EXTFdistance	0.000	-0.001	-0.004	-0.001
	(0.001)	(0.001)	(0.007)	(0.007)
Constant	6.194	0.721	9.748**	0.558
	(0.448)	(0.698)	(3.609)	(3.626)
Wald χ^2 /F-stat.	8.13***	70.69***	1.10	1.86**

Note that we

controlled for other variables but reported only the coefficients of the variable (EXTFdistance) tested regression constants and joint significance test statistics for lack of space.

Appendix 4D: Endogenous Treatment Effect (eteffects) Model-based Adoption Effects

Outcome variable	Potential mean outcomes		ATE	ATT
	Adopters	Non-adopters		
logFGC (in GHS) per AE	6.069 (0.162)	6.025 (0.124)	0.044 (0.201)	0.366 (0.269)
Food Gap (# of months)	0.848 (0.095)	0.725 (0.066)	0.122 (0.116)	0.362 (0.212)
Workdays of Female labor/acre of maize	11.616 (0.988)	8.672 (0.863)	2.944 *** (1.253)	6.399*** (1.852)
Male labor used per acre of maize plot	16.961 (0.975)	13.301 (1.250)	3.660 ** (1.580)	2.187 (2.801)

Standard errors in parenthesis. We used log-linear specification for LogFCE and linear for reciprocal food gap, female labor and male labor. Poisson model of untransformed FG using the **etpoisson** Stata command gave identical results to that of the **eteffects** command on the reciprocal food gap.

Chapter 5

Composting Waste for Agriculture in Northern Ghana: Rural Farmers' Willingness to Pay for Essential Attributes

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Abstract

Agricultural agencies in northern Ghana try, with limited success, to prime rural farmers to produce and use organic fertilizers while municipal solid waste (MSW) compost producers in cities lack adequate demand to sustain production. This study carried out a discrete choice experiment to examine potential demand among rural smallholder farmers through their willingness-to-pay for relevant MSW compost attributes and market access. Using the generalized multinomial logit (G-MNL) model, several specifications consistently showed that the attributes significantly influence farmers' decision to buy MSW compost. The results also show widely varied preferences for attributes across individual farmers, mainly due to unobserved factors. The study further reveals that, for a 50kg compost bag, farmers are willing to pay, on average, GHs9.43 for brand/label, GHs5.76 for pelletized compost, GHs4.49 for delivery at the community, and GHs2.49 for sales during cash windfall. Farmers face average disutility, valued not less than GHs33.36 for deciding not to buy a bag. This indicates that some essential attributes other than those in the survey influence farmers not to buy if the price equals or exceeds GHs33.36. The findings suggest the need to subsidize MSW compost by more than 50%, pelletize and brand/label compost well as well as make it accessible to rural farmers during their cash windfall.

Keywords: Discrete choice experiment, compost attributes, G-MNL model, northeastern Ghana, willingness-to-pay

5.1 Introduction

The northern part of Ghana has a predominantly agrarian employment structure with low income earning capacity. The agriculture sector employs about 74% of the working population, over 80% of whom are rural households (Government of Ghana, 2015 Amikuzonu and Donkor 2012). The farmers have a long tradition of grain production. However, with increasing constraints on arable land, farming systems in the area have failed to respond to food demand increases for the past two decades. Among the reasons accounting for the situation is soil degradation following continuous exploitation of farmlands without fallowing or adequate nutrient replacement (AfDB, 2006; Braimoh and Vlek, 2006; Agwe *et al.*, 2007; Nkonya *et al.*, 2015). Soil degradation is exacerbated by prevailing semi-arid conditions, limiting recovery of vegetative cover after human-induced changes and thus slowing organic matter accumulation. This has resulted in a generally low organic matter content of soils in the northern savannah zones (Braimoh and Vlek, 2004; Owusu *et al.*, 2020).

Organic fertilizers provide essential natural carbons for sustaining the physical, chemical, and biological properties of soils under continuous and intensive cultivation (Vanlauwe, 2015; Sudradjat *et al.*, 2018). For this purpose, the Ministry of Food and Agriculture (MoFA), in collaboration with non-governmental organizations (NGOs), has been assisting farmers, through capacity-building programs, to use organic soil amendments to improve their soil conditions. However, the programs seem to have had minimal effect in encouraging organic fertilizer use due to a general lack of biomass in the area (GIZ, 2013).

Meanwhile, city waste management authorities grapple with sanitation challenges posed by mounting municipal solid waste (MSW), about 84% of which is biodegradable (GIZ, 2013; Pradhan *et al.*, 2013; Republic of Ghana, 2015). Ineffective methods of collection and disposal of waste characterized the Ghanaian waste management systems in the urban centers (Danso *et al.*, 2002). Waste usually piles up in cities, provoking unsightly views, polluting both water and air, while breeding vectors of diseases like malaria, typhoid, diarrhea, cholera, dysentery (Folefack, 2008).

However, the biodegradable component is a rich source of nutrients with very high potentials for closing the soil nutrient recycling loop, improving cost recovery within the waste sector, and creating viable businesses with job opportunities by converting the waste to organic fertilizers (Danso *et al.*, 2017). Thus, converting organic waste into agricultural compost resolves the challenge of soil nutrient depletion. Controlled composting of organic waste generated in cities

provide organic fertilizers the rural farmers need while reducing the pollution in cities associated with improper disposal of waste (Danso *et al.*, 2002; 2006; Galgani *et al.*, 2014). Ghana recognizes the role of composting MSW in dealing with unsanitary conditions plaguing cities and strategic policies for reducing GHG emissions through open landfills (Galgani *et al.*, 2014; Republic of Ghana, 2015). Consequently, for the last two decades, government agencies have paid much attention to creating an enabling environment for the private sector to invest in MSW composting for agricultural use. This led to the establishment of composting enterprises collaborating with Zoomlion Ghana Ltd (the lead national waste management company).

Compost stations like DeCo Compost in Tamale are sited in suburbs of cities to efficiently absorb the high tonnage (nearly 250 tons) of daily waste (Pradhan *et al.*, 2013). However, composting around cities implies that the compost is physically accessible to urban and peri-urban gardeners but not rural farmers who rather require substantial quantities of the input for grain fields (Folefack, 2008). Studies (e.g., Danso *et al.*, 2005) have shown that composters cannot market their output to farmers beyond a 40 km radius without incurring losses because of high distribution costs. Yet, demand from the urban and peri-urban compost users falls short of quantities required to clear supply from composters, should composters operate at waste-clearing capacities (Danso *et al.*, 2006; Folefack, 2008; Agyekum *et al.*, 2014). Thus, composters cut back on production to minimize losses, meaning the object of composting MSW for sustainable agriculture cannot be achieved under free-market conditions (Danso *et al.*, 2006).

In 2016, compost producers drew the government's attention to their increasing losses due to limited compost demand. They called for the inclusion of organic fertilizers in the national fertilizer subsidy program to make their compost affordable to resource-poor farmers. Subsequently, the government-subsidized compost sales price by 50%, beginning in the 2017 crop season (MoFA, 2017). However, this subsidy can increase effective demand only to the extent that users can access the input. Extending the compost market to rural farmers creates the demand needed to stimulate MSW composting to a level at which it can achieve its purpose. Hence, there is a need to improve access to rural farm input markets, where the farmers can physically access the input.

Increasing access implies distribution and other marketing costs, which eventually will be passed on to farmers through pricing. To gauge potential patronage for MSW compost requires information about price and other attributes valued by farmers. However, since the rural farmers have not had access to commercial MSW compost, it is unknown what attributes of MSW compost

will influence their demand. Hence, the need to identify and evaluate qualities of the input that can affect farmers' demand before investing in improving market access (Agyekum *et al.*, 2014). Unfortunately, studies on MSW compost demand (e.g., Ampadu, 2001; Danso *et al.*, 2002; 2006; Folefack, 2008; and Agyekum *et al.*, 2014, Kuwornu *et al.*, 2017; Danso *et al.*, 2017) in Sub-Saharan Africa have mainly concentrated on the urban/peri-urban minority users. Also, except for Agyekum *et al.* (2014) and Danso *et al.* (2017), studies have generally employed contingent valuation (CV) despite the extensive criticisms that it overestimates farmers' willingness to pay (WTP) (Danso *et al.* 2006). There has not been any empirical analysis of rural farmers' WTP for MSW compost using discrete choice experiments in Ghana to the best of our knowledge.

Thus, our study sought to a) estimate rural farmers' WTP for MSW compost relevant through attributes and b) examine how farmer characteristics relate to preference variations, using a discrete choice experiment. The study's findings provide useful information to guide current and potential investors in the MSW composting sector and highlight how the government needs to intervene to promote the public good (cleaner cities) that MSW composting provides. The study adds spatial and strategic marketing dimensions to the literature on the current debate on closing the rural-urban nutrient cycle in Sub-Saharan Africa through composting waste from urban centers for agricultural use. Biomass

The rest of the paper is organized as follows. The next section (section 2) outlines the methodological approach, including sampling, data collection, and exposition on the choice model we applied. Section 3 presents econometric results by variants of the model, including average willingness-to-pay estimates from a willingness-to-pay space specification. The final section discusses the empirical findings and draws policy conclusions.

5.2 Methodology

5.2.1 Survey development, discrete choice experiment and farmer characteristics

The data we used for this study was collected through a multistage sampling survey of smallholder maize farmers from 52 communities across eight districts of the Northeast and Upper East Regions of Ghana. The area was chosen for this study because it experiences the most degraded soil conditions. Farmers in the area have received substantial support to use organic amendments to sustain soil health. For the Northeast Region, communities were selected from East and West Mamprusi districts clustered around Presbyterian Agriculture Station (PAS) at Lagbinsi. Communities chosen for Bunkpurugu and Yunyoo-Nasuan districts were also clustered around Bunkpurugu town. For the Upper East Region, communities in Tempene and Pusiga districts were

clustered around Wornyanga, while those for Garu and Binduri districts were centered between the towns of Garu and Binduri.

The farmers responded to a two-section structured questionnaire during a personal interview (PI) with us. The first part constitutes a discrete choice experiment, which elicited farmers' choices for MSW compost (see Table 5.1), while the final section sought information on farmers' background characteristics (see Table 5.3). The hypothetical bags, representing alternatives in the choice experiment, were defined by compost/market access attributes, including form, brand/label on packages, price, point of compost delivery, and sales period.

Following Danso *et al.* (2017), we identified and selected the MSW compost attributes in this study in three steps. A review of previous empirical studies (e.g., Folefack, 2008; Agyekum *et al.*, 2014; Bienenfeld, 2014; Danso *et al.*, 2017; Kuwornu *et al.*, 2017) guided the first-step for identifying potential attributes. We compiled an initial list of six attributes from these previous studies, including nitrogen-fertilizer fortified MSW compost. However, second-step validation of the attributes through discussions with experts (DeCo Compost, PAS management, and farmer-group leaders) revealed that all MSWcompost currently are fortified with nitrogen fertilizer. Hence, we maintained only five attributes, including price. Information on relevant attributes and their critical levels was obtained through focus group discussions with two farmer groups (Zou, 2011; Danso *et al.*, 2017; and Ahmed *et al.*, 2020). Our discussion with farmer representatives revealed that each attribute, except price, has realistically two qualitative levels. DeCo Compost management provided information on market and price attributes in Tamale.

Considering the prevailing market price, transport costs and government subsidy on the sales price, we set three potential price levels in the choice experiment. At the survey time (May-August prevailing 2018), the three price levels reflected the low-end price under 50% government subsidy on the sales price and high-end price, made up of the sales price plus average transport cost for a bag from DeCo compost station to communities in the study area. Table 5.1 shows the MSW compost attributes and their levels for evaluating the utility farmers derive from the input.

For each attribute, we considered some intuitive hypotheses relating it to farmers' behavior as input users. Generally, pelletizing MSWcompost reduces its bulkiness and improves product structure for easy dispensing during application. Pelletized compost is easier to apply, with much precision than powder or lumped compost (Danso *et al.*, 2017; Kuwornu *et al.*, 2017); thus, farmers will prefer pelletized to unpelletized MSW compost. Brands and labels give farmers information on various aspects of the fertilizer, including product identity and nutrients

composition, which influence both descriptive and inferential beliefs about the compost value. Favorable farmers' perceptions about the overall quality of MSW compost, in turn, influence purchasing intention (Larceneux and Carpenter 2008). Thus, farmers are expected to be more likely to buy MSW compost in branded/labeled than unbranded /unlabeled form (Agyekum *et al.*, 2014).

Table 5.1: Compost attributes and levels in the discrete choice experiment

Attribute	Description of Attribute	Levels	Reference Level
Form	How the fertilizer has been formed to allow easy application	1. Unpelletized 2. Pelletized	Unpelletized
Brand/Label	Whether the bag is branded or not.	1. Unbranded bag 2. Branded bag	Unbranded bag
Period of Sales	The period for compost sales within cropping-cycle	1. At planting time 2. At preceding crop harvest	At planting time
Delivery Point	Where farm will take delivery of fertilizer they buy	1. At farm input shop 2. At community	farm input shop
Price	^a Amount in Ghana Cedis per 50kg bag of DeCo MSW compost	1. GHs 15 2. GHs 25 3. GHs 35	Continuous

^a*Ghana Cedis, GHs6.5 = \$1 at the survey time.*

Duflo and Robinson (2011) observed that if fertilizer is offered to farmers during cash wind-fall after preceding crop harvest season, small but time-limiting price discounts could induce sizeable demand increases comparable to heavy subsidy later in the farming season. This means that the period for MSW compost sales, relative to farmers' cashflow cycle, is valuable to a farmer who would use the compost. Hence, we hypothesized that farmers prefer to buy MSW compost even at high prices when they have cash from previous harvest sales than later in the farming season.

Deciding the type, how much, and where to buy fertilizer involves cost. Since farmers always discount future utility, those who plan to use fertilizer defer incurring the decision cost until the last possible moment, no matter how little the cost may be (Duflo and Robinson, 2011). Danso *et al.* (2005) found that transporting commercial compost from production sites even to the urban/peri-urban users limits effective demand for MSW compost by farmers in Ghana. Folefack (2008) reported that the transport cost problem is worse for village farmers and called for subsidies to boost supply and demand for compost among rural farmers in Cameroon. This means that farmers are more likely to purchase commercial compost if they can obtain it from within their community than from somewhere else. Of course, the last attribute is the price for MSW compost with the usual hypothesis from the law of demand: farmers are expected to buy more MSW compost at a lower price than they would at a higher price. Hence lower price levels are preferred to higher price levels.

In this multi-attribute compost choice experiment, the efficiency and accuracy of preferences, for that matter, WTP estimates, significantly depended on the design to be used (Kuhfeld *et al.*, 1994; Lusk and Norwood 2005; and Street *et al.*, 2007). Yet, no single design maximizes efficiency without compromising attribute orthogonality required for estimation (WHO, 2012). To enhance the reliability of estimates, we adopted the sequential approach to design, following Bliemer and Collins (2016) and Bello and Abdulai (2016) by creating, first, an orthogonal fractional factorial design (Hensher *et al.*, 2005). This initial design was used for a pilot choice experiment on a sample 20 members of farmer-groups that we interacted with during attributes identification.

Conditional logit preference estimates obtained from the pilot sample data became our Bayesian priors for designing a final D-efficient experiment to maximize efficiency and robustness of estimates (Huber and Zwerina, 1996; Bliemer and Collins, 2016). A D-efficient fractional factorial from a full factorial design of $24 * 3 = 48$ alternative profiles gave six alternative profiles for estimating the attributes' main effects. We added two balanced profiles for a degree of freedom to test attribute interactions and one dominant profile to check if farmers applied heuristics in making choices. Therefore, nine choice sets were presented to each respondent during the choice experiment. The last choice set, with the dominant alternative, was excluded from the analysis. Table 5.2 below shows an example of choice sets presented to the farmers. Heuristics

In all, 398 representative households completed the questionnaire, providing data on both stated compost preferences and socio-economic characteristics that could influence their MSW compost choices. Of the total sample of farmers interviewed, only 87 (21.8 %) were females. More than half of the farmers were between 25 and 60 years old, with an average sample age of 42.28 years. On average, they have 5.21 years of formal education and earn a meager average monthly income of about Ghs420, but have to cater for an average of 6 persons in a household. About 40 percent of them make their income, not only by farming but also through other activities like craftwork. The farmers generally live about 1.5 hours walk away from the nearest market, having physical and pecuniary constraints to accessing inputs. Hence, about 50% of them have had to use an organic fertilizer at one time or the other. The summary statistics of these characteristic variables are shown in Table 5.3.

Table 5.2: Example of choice sets presented to farmers to elicit preferences

Hypothetical bias mitigation: Cheap Talk			
<p>Studies show that people act in a different way when they face hypothetical decisions. For example, some people state a price they would pay for an item, but they do not pay the item's price when they see this product in a grocery store. There can be several reasons for this different behavior. It might be too difficult to measure how buying an item affects the household budget. Another possibility is that it might be challenging to visualize themselves getting the product from a grocery store shelf and paying for it. Do you understand what I am talking about? We want you to behave in the same way you would if you had to pay for the product and take it home. Please consider how much you want the compost bag, instead of its alternatives or constraints that might make you change your behavior. Please try to put yourself in a realistic situation.</p>			
Attribute	Compost bag "A"	Compost bag "B"	Opt-out "C"
Form	 Unpelletized compost	 Pelletized compost	<p>If alternative A & B are the only options available to me, I will not buy MSW compost</p>
Brand/Label	 Branded/Labeled	 Unbranded/unlabeled	
Period of Sales	 At planting time	 At preceding crop harvest	
Delivery Point	 At village/community	 At the nearest input shop	
Price	GHs35	GHs25	
Choice	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	

Table 5.3: Major socio-economic characteristics of sample farmer

<i>Characteristic Variable</i>		<i>Mean/Freq(%)</i>	<i>Min.</i>	<i>Max.</i>	<i>Std. Dev.</i>
Gender of Household head	Females	21.8			
	Males	78.2			
Age of household head (number of years)		42.28	20	75	14.11
Education of household head (years of formal schooling)		5.21	0	22	6.01
Total monthly household income (1000s of Ghana Cedis)		0.42	0.08	2.20	0.29
Household size (number of persons)		5.58	1	20	3.16
Walking distance to the nearest input market(in minutes)		90.03	5	190	41.04
Off-farm extra income work participation (yes /no)		39.84			
Organic fertilizer experience (yes / no)		50.4			
<i>Have some means of transport</i>	None	21.68			
	Bicycle	40.68			
	Motorcycle	36.52			
	Tricycle	1.17			

5.2.2 Conceptual framework and Econometric Model

The use of McFadden's (1974) random utility model to estimate consumer utility has become commonplace in analyzing discrete choice experimental data (Hills *et al.*, 2020; Osburn *et al.*, 2020), especially for estimating utility weights on different attributes. The model supposes that farmers maximize the latent utility from choosing compost bags while making trade-offs between the bags' characteristics. Typically, the model is derived within a linear framework and is expressed as a function of a farmer choosing compost bags with given attribute profiles in various choice scenarios. The utility, U_{ijt} that farmer i derives for choosing an alternative bag j from choice situation t , is generally decomposed into a deterministic component V_{ijt} , which is observable to the analyst and a stochastic unobservable part ε_{ijt} and specified as;

$$U_{ijt} = V_{ijt} + \varepsilon_{ijt}, i=1, \dots, N; j=1, \dots, J, t=1, \dots, T \quad , \quad (1)$$

where ε_{ijt} is the stochastic error term motivated by farmer-heterogeneity in preference for unobserved attributes (Hensher *et al.*, 2015; Bello and Abdulai, 2016; Osburn *et al.*, 2020).

The deterministic component V_{ijt} is, in turn, a function of observed attributes, \mathbf{X}_j of chosen the compost bag, including price, pelletized compost, branded sack, sales at preceding harvest time, and delivery at community sales point and a dummy variable D_i for an opt-out choice. Thus, U_{ijt} is re-defined as;

$$U_{ijt} = \beta'_i x_{ijt} + \alpha_i D_{ijt} + \varepsilon_{ijt} \quad , \quad (2)$$

where β_i is a vector of the utility weights associated with the attribute variables and α_i is the utility farmer i derives from opting not to buy compost. If $prob(U_{ijt} > U_{iqt})$ for all $q \neq j$ the probability of farmer i choosing bag j under conditional logit distribution is specified as;

$$P_{ni} = \frac{\exp(\beta x_{ni})}{\sum_{q=1}^J \exp(\beta x_{qnt})} \quad (3)$$

The conditional function assumes that ε_{ijt} is independently and identically distributed type-1 extreme value, meaning no interaction between alternatives in choice situations and that preferences for attributes are homogeneous. These lead to the further restrictive and often empirically unrealistic independence of irrelevant alternative (IIA) assumption (Fiebig *et al.*, 2010; Kassie *et al.*, 2017). While these assumptions make the model intuitively desirable at the individual level, they are often invalid at the sample level (Ben-Akiva and Bierlaire, 1999; Carson and Czajkowski 2012). Thus, in empirical research, it is usual to apply models that relax IIA and the related assumptions to obtain realistic estimates.

Depending on whether we assume discrete or continuous random utility weights on observed attributes, there are two popular approaches by which we can relax the IIA assumption. The latent class model (LCM) and the random parameter logit (RPL) model. For details of the LCM, see Zhang and Sohngen (2018). By specifying the RPL model, we permit the utility weights on attributes to vary across farmers with a continuous distribution. In this case, the utility weight β_i for a given attribute, including α_i in (2) will be $\beta_i = \beta + \eta_i$ (Osburn *et al.*, 2020), with the utility function then being (Fiebig *et al.*, 2010):

$$U_{ijt} = (\beta + \eta_i)' \mathbf{X}_{ijt} + \varepsilon_{ijt} \quad (4)$$

where β is a vector of mean attribute utility weights in the population, and η_i is the farmer i 's specific deviation from the respective mean.

Theoretically, the mixing distribution for β_i in (4) can be anything, but researchers usually specified a multivariate normal distribution (Fiebig *et al.*, 2010; Zhang and Sohngen, 2018). Thus, Louviere *et al.* (2008), Fiebig *et al.* (2010), and many others have criticized the RPL model. They noted that empirical distribution of utility weights by the RPL model usually does not approximate normal distribution, as many researchers assume. Moreso, preference heterogeneity in most choice contexts are captured better as scale-heterogeneity, where the scale of the idiosyncratic error term ε_{ijt} is greater for some farmers than others. In the scale heterogeneity logit (S-MNL) model, the scale of the error term (σ), instead of being normalized to one, is made explicit as:

$$U_{ijt} = \beta' \mathbf{X}_{ijt} + \varepsilon_{ijt}/\sigma \quad (5)$$

The model in (5) means that σ is heterogeneous in the population. Thus, we denote the value for farmer i by a scalar random variable, σ_i , and obtain:

$$U_{ijt} = \beta' \mathbf{X}_{ijt} + \varepsilon_{ijt}/\sigma_i, \quad (6a)$$

which, when multiplied through by σ_i gives the final S-MNL as:

$$U_{ijt} = \sigma_i(\beta)' \mathbf{X}_{ijt} + \varepsilon_{ijt} \quad (6b)$$

Within farmer-population, the RPL model in (4) can also be scale-heterogeneous, with scale affecting only β , resulting in a model that combines equation (4) and (5) as:

$$U_{ijt} = (\sigma_i \beta + \eta_i)' \mathbf{X}_{ijt} + \varepsilon_{ijt}, \quad (7)$$

or both β and η , giving rise to a scaled random parameter logit model, specified as;

$$U_{ijt} = \sigma_i(\beta + \eta_i)' \mathbf{X}_{ijt} + \varepsilon_{ijt}, \quad (8)$$

Keane (2006) and Keane and Wasi (2013) explained that (4) to (8) are special cases that can be nested in a generalized multinomial logit (G-MNL) model. However, Hess and Train (2017) argued that the RPL specification in (4) captures all heterogeneity forms in data. Thus, a typical G-MNL model is a restricted form of the RPL that allows for scale heterogeneity but not other sources of correlation. While this argument rages on, Fiebig *et al.* (2010) and Greene (2018) have shown that the G-MNL model nests a wide range of special cases, including (2) to (8). These can be explored to identify the source(s) of heterogeneity (Gu *et al.*, 2013). This has made the G-MNL model very appealing to empirical researchers (Zhang and Sohngen, 2018; and Ahmed *et al.*, 2020). The G-MNL model is given as:

$$U_{ijt} = [\sigma_i\beta + \gamma\eta_i + (1 - \gamma)\sigma_i\eta_i]'X_{ijt} + \varepsilon_{ijt}, \quad (9)$$

where the parameter γ determines how the standard deviation of the random utility weights is scaled. Usually, γ is constrained to be between 0 and 1, but Keane and Wasi (2013) argued that there is no reason to do so. Subsequently, in their Stata code, Gu *et al.* (2013) allowed it to take any value.

If $\gamma \rightarrow 0$, we obtain a scaled-RPL in (8) known as G-MNL-II, in which the standard deviations of farmer-specific deviations, η_i are scaled proportionally to their mean attribute weights. On the other hand, if $\gamma \rightarrow 1$, we obtain (7), known as G-MNL-I, where only the mean-attribute weights are scaled. Furthermore, if $\sigma_i = \sigma = 1$ in either (7) or (8), the G-MNL becomes the RPL model (MIXL) in (4), and when η_i does not vary (i.e., $\text{var}(\eta_i) = 0$), the S-MNL model in (6b) occurs. Both the MIXL and S-MNL specification can also nest the basic multinomial logit (MNL) model, where, in the MIXL, $\text{var}(\eta_i) = 0$ and in the S-MNL, σ_i becomes $\sigma = 1$ (Fiebig *et al.*, 2010; Greene, 2012; Kassie *et al.*, 2017; Ahmed *et al.*, 2020).

The individual-specific scaling factor (σ_i) of the idiosyncratic error term is a positive log-normally distributed value, defined as $\sigma_i = \exp(\bar{\sigma} + \tau\varepsilon_{0i})$, where $\varepsilon_{0i} \sim N(0,1)$, $\bar{\sigma}$ is a mean parameter of scale variance, and τ is the coefficient on the unobserved scale heterogeneity (ε_{0i}). To explain scale variation across farmers, we can make σ_{it} a function of farmer characteristics and or some measures of entropy of choice occasions (Fiebig *et al.*, 2010; Gu *et al.*, 2013). Thus, we express choice situation-specific scale, σ_{it} as;

$$\sigma_{it} = \exp(\bar{\sigma} + \theta'z_{it} + \tau\varepsilon_0), \quad (10)$$

where z_i is a vector containing interaction terms between choice attributes and farmer-characteristics, and θ denotes a set of parameters explaining observed heterogeneity in the scale factor. Since the integral of G-MNL log-likelihood

$$LL(\beta, \gamma, \tau, \theta, \Sigma) = \sum_{i=1}^N \ln \left\{ \int \prod_{t=1}^T \prod_{j=1}^J \Pr(\text{choice}_{it} = j | \beta_i)^{y_{itj}} p(\beta_i | \beta, \gamma, \tau, \theta, \Sigma) d\beta_i \right\} \quad (11)$$

has no closed-form; it must be numerically evaluated using the maximum simulated likelihood estimator. We used the simulated likelihood estimator coded by Gu *et al.* (2013) in Stata. The simulated log-likelihood (SLL) is given as;

$$SLL(\beta, \gamma, \tau, \theta, \Sigma) = \sum_{i=1}^N \ln \left\{ \frac{1}{D} \sum_{d=1}^D \prod_{t=1}^T \prod_{j=1}^J \Pr(\text{choice}_{it} = j | \beta_i^{[d]})^{y_{itj}} \right\}, \quad (12)$$

where $\beta_i^{[d]} = \sigma_i^{[d]} \beta + \{\gamma + \sigma_i^{[d]}(1 - \gamma)\} \eta_i^{[d]}$ and $\sigma_i^d = \exp(\bar{\sigma} + \theta_i + \tau \varepsilon_0^{[d]})$. $\eta_i^{[d]}$ is a k-vector generated from MVN(0, Σ) and $\tau \varepsilon_0^{[d]}$ is a N(0,1) distributed scalar drawn using *Halton* and pseudorandom draws, respectively. $d = 1, \dots, D$ refers to draws during the simulation. The simulated choice probability then assumes the function $\Pr(\text{choice} = j | X_{it}) = \frac{1}{D} \sum_{d=1}^D \frac{\exp(\sigma^d \beta + \gamma \eta^d + (1 - \gamma) \sigma^d \eta^d) X_{ijt}}{\sum_{k=1}^J \exp(\sigma^d \beta + \gamma \eta^d + (1 - \gamma) \sigma^d \eta^d) X_{ikt}}$ (Fiebig *et al.*, 2010).

It is empirically appealing to re-parameterize the conditional preference-spaced (PS) random utility choice model and estimate it in willingness-to-pay (WTP) space (Ahmed *et al.*, 2020). Modeling choice in WTP space is desirable because one obtains reasonable estimates of WTP directly as model coefficients, instead of deriving from utility weights after estimating PS model (Fosgerau 2007; Scarpa *et al.* 2008; Fiebig *et al.* 2010; Hensher and Greene 2011; Greene, 2018). Also, WTP estimates obtained from WTP space are better normally distributed than those from the SP specification. Thus, following Fiebig *et al.* (2010) to recast the G-MNL model in WTP space, we let $\gamma = 0$ (G-MNL II), constrain $\tau = 0$, and normalize the price coefficient to 1 to obtain the WTP space model estimates.

For this study, we explored the data for an appropriate model by fitting the full G-MNL (i.e., equation 9) and three other special cases for the compost choice model. Next, we estimated heterogeneity-in-scale models, excluding the G-MNL $\tau = 1$. Finally, by fitting their indexes, we chose the best specification (G-MNL-II) and re-casted it in WTP space to evaluate farmers' willingness to pay for compost attributes directly. We captured the opt-out decision as a dummy variable labeled NONE, which equals one when a farmer chooses not to buy compost (use status quo fertilizer type). Since our experiment is unlabelled, the opt-out and constant-utility dummies have alternate values of zero and one for each observation, resulting in perfect negative collinearity. Hence, only one of them (NONE) is estimated in the model.

5.3 Empirical Results

Here we present the empirical results for G-MNL model estimates for compost bag choice model, heterogeneity-in-mean preference model, and WTP estimates in WTP-space. G-MNL ($\tau = 1$) model gave significantly higher estimates with the worst fit performance than the other three specifications of the choice model. Thus, we did not include it in subsequent exploratory estimations. The remaining models- full G-MNL, G-MNL I, and G-MNL II - gave very similar estimates, but the G-MNL II produced the best model fit indexes in both the choice and the heterogeneity-in-mean models. Thus, we re-casted only the G-MNL II in WTP space to directly obtain empirically plausible WTP estimates (Scarpa *et al.*, 2008; Fiebig *et al.*, 2010; Kassie *et al.*, 2017). All specifications assumed a theoretically-consistent lognormal distribution for price and normal distribution for other attributes' parameters.

5.3.1 G-MNL model results

Table 5.4 presents econometric results of the G-MNL choice model for four different specifications. Several things are worth noting regarding the estimates: the signs and magnitudes of the estimated coefficients and their standard deviations are fairly robust across the models (i.e., full G-MNL, G-MNL-I, and G-MNL-II) except for the G-MNL($\tau = 1$) specification with all the mean estimated coefficients for attributes having the expected signs. The different model specifications consistently showed that the studied attributes significantly affect farmers' decision to buy compost. The coefficients in the formulations are comparable in terms of order and direction of influences on farmers' compost choice and the significance levels. Notably, the mean coefficients of full G-MNL and G-MNL-II models are almost identical for all attributes. The G-MNL-I model tends to have lower coefficients with statistically insignificant heterogeneity for the opt-out decision. The fourth model with a restriction on τ (G-MNL ($\tau = 1$)), on the other hand, resulted in higher coefficients, both for mean parameters and standard deviations.

The models also revealed substantial heterogeneity around estimated coefficients for all compost attributes, indicating the importance of accounting for variations in preference for MSW compost attributes across farmers (Zhang and Sohngen, 2018). We see heterogeneity from the significant standard deviations of coefficient vector, $\boldsymbol{\eta}$ (unobserved heterogeneity) and the scale parameter (τ). It is also worth noting that preference heterogeneity around the period of sales attribute is generally low across models but insignificant in G-MNL ($\tau = 1$), where heterogeneity around mean preference for pelletized compost is also unusually negative. An overall comparison of model performance using AIC, BIC, and the likelihood dominance criterion, reveals that full G-MNL and G-MNL-II outperform the other specifications.

Table 5.4: G-MNL model Estimates for compost choice

Variable	FULL G-MNL		G-MNL I($\gamma = 1$)		G-MNL II($\gamma = 0$)		G-MNL ($\tau = 1$)	
	(β)	Error	(β)	Error	(β)	Error	(β)	Error
Mean preference								
Price	-0.059***	0.005	-0.054***	0.004	-0.059***	0.005	-0.091***	-0.009
Form	0.329***	0.033	0.303***	0.027	0.327***	0.032	0.487***	-0.049
Brand/Label	0.567***	0.052	0.499***	0.037	0.558***	0.050	0.856***	-0.077
Period	0.160***	0.032	0.137***	0.027	0.157***	0.031	0.237***	-0.048
Delivpoint	0.253***	0.031	0.229***	0.026	0.250***	0.031	0.393***	-0.051
None	-1.997***	0.134	-1.825***	0.088	-1.978***	0.128	-2.967***	0.206
Heterogeneity in mean (η)								
Price	0.043***	0.005	-0.256***	0.037	0.042***	0.005	-0.069***	-0.009
Form	0.315***	0.042	0.421***	0.042	0.312***	0.042	-0.258***	-0.070
Label	0.479***	0.050	0.010***	0.069	0.474***	0.049	0.904***	-0.120
Period	-0.104*	0.056	-0.139**	0.064	-0.109**	0.054	0.130***	-0.087
Delivpoint	0.198***	0.061	1.458***	0.147	0.199***	0.060	0.476***	-0.087
None	1.453***	0.182	0.063***	0.066	1.424***	0.157	2.243***	-0.301
Tau (τ)	0.389***	0.103	0.036***	0.004	0.375***	0.106	1	fixed
Gamma (γ)	-0.134	0.203					-0.543***	0.110
#Parameters	14		13		13		14	
LL	-2910.5		-2916.8		-2910.7		-2938.1	
Pseudo R^2	0.253		0.252		0.253		0.246	
AIC	5848.9		5859.7		5847.3		5902.2	
BIC	5950.9		5954.3		5942.0		5996.9	
Observations	9,552		9,552		9,552		9,552	

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Based on the G-MNL-II model's estimates, brand/label on compost sacks is the most influential compost attribute affecting farmers' purchasing decision, followed by a pelletized form of compost. This means that farmers prefer branded/labeled bags containing pelletized compost to unlabeled bags with pelletized compost. Contrary to the MSW compost producer's anecdotal views, our results are in line with Agyekum *et al.* (2014) and Kuwornu *et al.*'s (2017) findings that these attributes are essential for compost demand even among generally illiterate farmers. Even though most sample farmers cannot read, they associate branded/labeled bags with trusted, high-quality compost; hence, enhanced utility from purchasing such bags. Pelletizing also eases and improves dispensing accuracy during compost application. Thus, farmers should prefer the pelletized to unpelletized compost (Agyekum *et al.*, 2014). The other traits influencing farmers' decision to purchase compost are delivery point and the period of compost sales. Farmers prefer taking delivery of compost at their community to going for it from the nearest input market. Physical access to markets is a challenge because of poor road network and consequent lack of reliable means of transport. Thus, the opportunity to purchase compost at farmers' community represents an added value to the compost.

The period during cropping season when compost is sold, though least significant, is also an important attribute influencing farmers' decision to buy the input. Early sales to farmers during cash windfall from previous crop harvests will attract many, especially farmers who are 'patient' to purchase compost. These early-season sales will be more attractive if it is combined with some price discounts (Duflo and Robinson, 2011). The coefficient of the price is, of course, negative, implying that higher price decreases farmers' utility from the compost. Thus, as per bag price increases from the lowest at GHs15 to the highest at GHs35, farmers' likelihood to purchase MSW compost decreases, other things being constant. Finally, there is a highly significant negative preference (-1.83, $p < 0.0001$) for opting not to buy compost, implying that farmers prefer the status-quo fertilizer type to MSW compost with attribute combination offering 1.83 units less utility. This is probably because of other valuable attributes of the status-quo not found in the MSW compost (Hills *et al.*, 2020). In other words, since the opt-out dummy variable is simply a reverse of choice decision dummy, the negative preference for opt-out captures (in the reversed direction) the average (constant) utility derived from MSW compost bag regardless of any attribute.

Figure 5.1 shows the increased probabilities resulting from improved levels of the compost attributes from their reference levels and in combination with a price at 50% subsidy. The graph shows that compost price subsidized 50%, combined with improved non-cost attributes, desirably increases compost uptake rate by 53% with transport cost to 88% with labeled compost bags. At that subsidized price, offering pelletized compost, farmers' cash windfall period sales and compost delivery at their community will increase the uptake rate by 85%, 83% and 84%, respectively. This indicates how vastly a subsidy, together with improved compost qualities and market access, stands to impact MSW compost uptake among rural farmers.

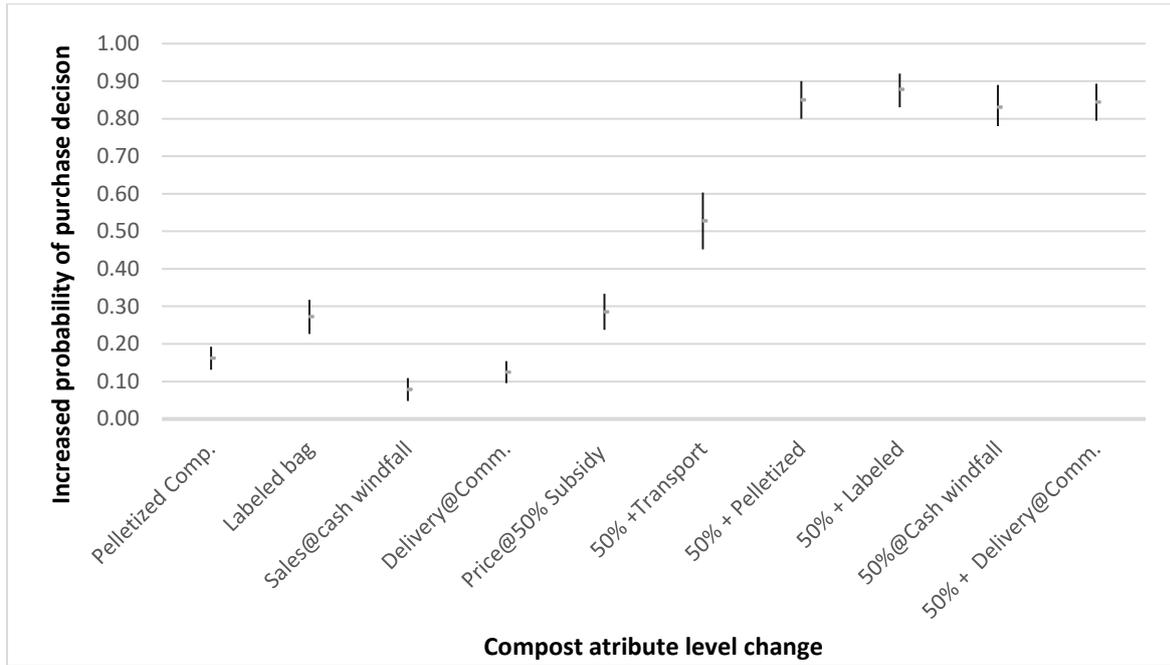


Fig.5.1: Marginal probabilities of uptake decision with attribute level change

5.3.2 Attribute preference heterogeneity and indicators

As noted above, the standard deviations of attributes' preferences and the scale parameter are significant. These reveal substantial heterogeneity across individual preferences for the attributes, except for the period of sales. The heterogeneity-in-mean preference specification explored source(s) of heterogeneity using farmer-characteristic and choice-attribute interactions as potential moderators Z_i of heterogeneity as given in equation (10). Table 5.5 presents comparable results of the scale heterogeneity model across the various G-MNL formulations (full G-MNL, G-MNL ($\gamma = 1$), and G-MNL ($\gamma = 0$)).

Though the full G-MNL model seems to have outperformed others (LL, Pseudo R^2 , and AIC), its γ estimate is not significant, meaning that the G-MNL ($\gamma = 0$) is appropriate for the data. Hence, our discussion below considered the restricted G-MNL ($\gamma = 0$) specification because it has also given the best explanatory model-fit index (BIC).

Gender, age, and household size of a farmer, organic fertilizer use experience, and the distance between a household and the nearest input market were found not to influence heterogeneity. On the contrary, education, income, off-farm job participation, and transport ownership significantly explained scale variations around average preferences for attributes. The years of formal education a farmer had had, explain some variation around the mean preference for pelletized (Form) compost. Farmers with many years of formal education are more interested in pelletized compost than those with few. Household income explains variation around the average level of preference

for not buying compost. High-income households prefer less not to buy compost than low-income households. It means that the unobserved compost attributes that lead farmers to opt-out of compost purchases are less important to farmers with high household income than those with low income

Table 5.5: Scale heterogeneity in mean parameter model estimates

VARIABLE	FULL G-MNL		GMNL-I ($\gamma = 1$)		G-MNL II($\gamma = 0$)	
	β	Error	β	Error	β	Error
Mean Preference						
price	-0.062***	0.006	-0.055***	0.004	-0.060***	0.006
form	0.327 ***	0.035	0.300***	0.028	0.326***	0.033
label	0.544 ***	0.061	0.495***	0.038	0.572***	0.055
period	0.141 ***	0.032	0.138***	0.028	0.159***	0.032
delivpoint	0.361 ***	0.060	0.334***	0.048	0.368***	0.056
none	-1.595***	0.133	-1.629***	0.122	-1.723***	0.150
Observed scale heterogeneity (θ)						
Pric*age	0.039	0.040	0.048	0.041	0.030	0.046
Pric*income	-0.098	0.055	-0.072	0.053	-0.085	0.061
Pric*offfarm	0.264***	0.062	0.187***	0.057	0.201***	0.064
Pric*edu.	0.102	0.095	0.121	0.193	0.136	0.152
Form*edu.	0.044	0.027	0.036	0.024	0.046*	0.027
Form*income	-0.033	0.030	-0.034	0.025	-0.031	0.028
Form*offfarm	0.072**	0.032	0.060**	0.028	0.063**	0.031
Label*edu	-0.003	0.036	-0.005	0.031	0.002	0.035
Label*offfarm	0.085**	0.042	0.066*	0.035	0.075*	0.040
Label*orgause	0.050	0.037	0.048	0.031	0.034	0.037
None*income	-0.166**	0.074	-0.104*	0.058	-0.128*	0.067
None*offfarm	0.334***	0.075	0.278***	0.065	0.312***	0.072
None*orgause	-0.142	0.117	-0.152	0.107	-0.135	0.116
None*transp.	0.375**	0.146	0.286**	0.134	0.307**	0.155
Period*offfarm	0.093	0.064	0.079	0.055	0.078	0.061
Delivpoint*transp.	-0.196**	0.078	-0.166**	0.065	-0.195***	0.074
Delivpoint*Mktdist.	0.091	0.059	0.077	0.049	0.079	0.054
Heterogeneity in mean (η)						
price	0.042***	0.005	0.037***	0.004	0.041***	0.005
form	0.309***	0.042	0.269***	0.039	0.300***	0.042
label	0.519***	0.056	0.427***	0.042	0.490***	0.054
period	-0.096	0.060	-0.075	0.062	-0.088	0.062
delivpoint	-0.192***	0.056	-0.130*	0.075	0.162*	0.098
none	1.353***	0.165	1.284***	0.134	1.325***	0.157
tau (τ)	0.322***	0.122	0.039*	0.068	0.330***	0.131
Gamma (γ)	-0.105	0.266				
No. of Parameters	30		29		29	
LL	-2903.2		-2897.3		-2885.5	
Pseudo R^2	0.261		0.258		0.260	
AIC	5822.8		5838.9		5829.0	
BIC	6041.3		6050.1		6040.2	
Observations	9,552		9,552		9,552	

Note.: *** p<0.01, ** p<0.05, * p<0.1. Other insignificant variables included in the scale heterogeneity function are household location variables and interaction terms of gender and household size, and choice attributes.

Off-farm job participation is significant and positively explains variations around average preferences for compost price, pelletized form, brand/label, and some unobserved attributes. Therefore, farmers with off-farm income are more interested in these traits, regardless of the price

level, than those without off-farm income sources. The variation around mean-preference for compost delivery point is explained by transport ownership. Farmers who own means of transport like a bike, motor, or tricycle tend to care less about taking delivery of compost in the community. This makes sense because those farmers can afford to transport their compost from the input market and, thus, trade-off delivery at the community for other attributes like a lower price. Transport ownership also explains but positive variation around average preference not to buy compost. This means that transport owners prefer unelicited compost attributes more compared to those without transport. Lastly, heterogeneity-in-mean preference models showed significant unobserved preference heterogeneities around the attributes, except the sales period.

5.3.3 *Farmers' Willingness-to-pay for MSW compost attributes*

Based on the estimates obtained in the G-MNL-II model formulations, the marginal value or willingness to pay (WTP) for improved levels compared to reference compost attributes levels were estimated in WTP space (Scarpa *et al.*, 2008; Fiebig *et al.*, 2010; Hensher and Greene 2011; Kassie *et al.*, 2017 Greene, 2018; Ahmed *et al.*, 2020). These WTP estimates represent additional prices a farmer has to pay for the improved attributes, such that utility, and for that matter, the choice probability remains unchanged. In other words, the WTP reflects the monetary values or premiums to be paid for improvement in the attributes.

The WTP estimates in Table 5.6 show that farmers in the study area value brand/label more than any other elicited attributes. This is followed by a pelletized form of compost, compost delivery at farmers' village, and sales at cash windfall periods, in that order. However, there is an average disutility valued at GHs 33.35 for a decision to buy a bag of compost. This indicates that, at GHs33.35/bag of MSW compost, an average rural farmer is undecided regarding purchasing MSW compost, and will opt, regardless of the attributes profile, if the price increases further.

The mean WTP estimates indicate that farmers are willing to pay a premium for brand/label that is 1.69 times what they are willing to pay for pelletized compost, 2 times the premium for delivery at the community, and 4 times that of early sales (during cash windfall). This shows the relative importance of brand/label over all the other compost attributes in attracting farmers to buy the input.

Table 5.6: Willingness to pay for MSWcompost attributes in WTP space

VARIABLE	G-MNL II ($\gamma = 0$) in WTP Space			
	Coefficient	Error	[95% Conf. Interval]	
Mean WTP (β_{wtp})				
Price	1	fixed		
Form	5.758***	0.544	4.601	6.698
Brand/label	9.427***	0.770	8.080	11.124
Period	2.494***	0.512	1.485	3.496
Delivpoint	4.487***	0.592	3.324	5.650
None	-33.36***	1.980	-37.430	-29.670
Heterogeneity in mean (η)				
Price	0.000	fixed		
Form	5.186***	0.717	3.582	6.42455
Brand/label	-8.274***	0.872	6.735	10.186
Previous harvest Period	-0.458	1.587	-3.475	1.889
Delivpoint	3.430**	1.053	-5.465	-1.649
None	14.127***	1.576	-17.179	-11.227
Constant (σ)	-2.973***	0.070	-3.105	-2.833
Tau	0	fixed		
No. of parameters			11	
LL			-2929.73	
Pseudo R^2			0.25	
AIC			5881.47	
BIC			5961.57	
Observations			9,552	

Note: Price and tau (τ) are constrained at one and zero, respectively, to define the model in WTP space. The sign of the estimated standard deviations is irrelevant: interpret them as being positive

Figure 5.2 shows the distributions of normal-mixing farmer-specific WTP estimates for the attributes. Brand/label (b) has the most widely distributed farmer-specific WTP estimates, followed by pelletized form (a) with the largest deviation, in that order. Few farmers (3%) showed negative WTP for these attributes, which means that for those farmers, compost pelletizing and branding combine with a negative implicit price to maintain utility from compost choices. The next attribute with significantly varying WTP estimates is delivery at the village, which except for two farmers, is positive and ranges from 0.84 to 9.21 Ghana Cedis. The WTP estimates for early period sales (c) are entirely positive and very narrowly distributed within the range of 2.2 to 2.9 Ghana Cedis per compost bag. With a spread within 1.5 cedi interval, the standard deviation around the mean (GHs 2.49) is not significant. Thus, WTP for sales during cash windfall seems fixed among the sample farmers.

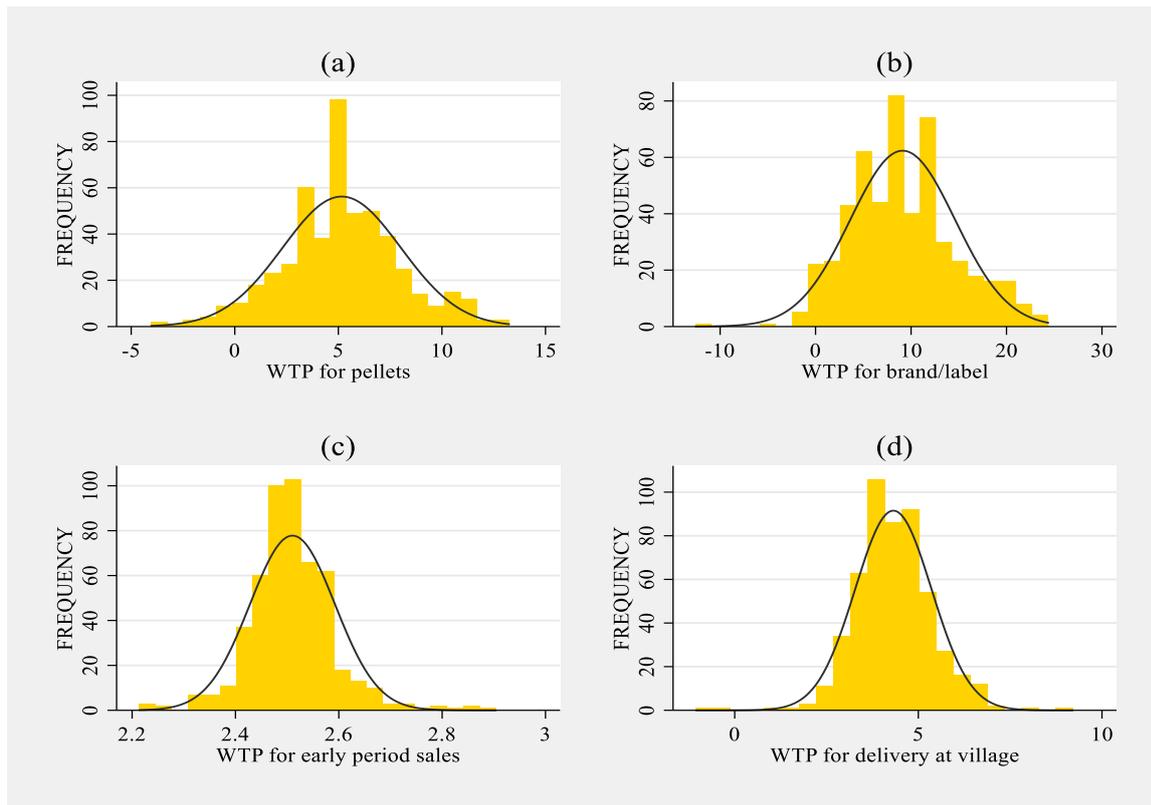


Figure 5.2: Distributions of farmer-specific WTP for MSW compost attributes

5.4 Discussion and conclusion

The Ministry of Food and Agriculture, in collaboration with NGOs, strives to build farmers' capacity to produce and use organic soil amendments in northern Ghana, while MSW compost producers in cities lack effective demand for their product. In order to remain in the social business of clearing public waste from cities, these composters need to reach out to the rural farmer-population for a broader market. Yet, successfully marketing commercial MSW compost to rural farmers requires knowledge of their willingness-to-pay. Farmers' willingness-to-pay for compost attributes essentially governs the attraction to the inputs. Therefore, it is vital to elicit such attributes and determine the implicit prices the farmers are willing to pay.

We used a discrete choice experiment to elicit preferences for access and product attributes of a hypothetical MSW compost and applied the G-MNL model to quantify implicit prices farmers are willing to pay for the attributes. Different specifications of the model consistently showed that the attributes we elicited in this study significantly affect farmers' decision to buy compost, with bag brand/label being the most preferred attribute. Preferences for the attributes broadly vary across individual farmers, except for the period/time of sales.

However, on average, the farmers face a disutility valued at GHs33.36 to decide not to buy the MSW compost. This disutility, measured by the willingness-to-pay for opt-out, is in absolute

value, equivalent to the average premium a farmer places on MSW compost bag regardless of the attributes elicited by the survey. This indicates that some vital status quo fertilizer attributes not included in our survey influence farmers to opt-out when MSW compost price equals or exceeds GHs33.36 (Hills *et al.*, 2020). We have no further information supporting any immediate reason for this result. However, our finding is at variance with Danso *et al.* (2002 and 2006) that demand for urban waste compost could be marginal due to cheaper yet nutrient-rich alternative soil amendments. In this case, no alternatives other than mineral fertilizer exist in the study area for the rural farmers. The disutility value being about half the price of subsidized mineral fertilizer may indicate that farmers contrast the expected utility of MSW composts with that of mineral fertilizer.

Compost manufacturers need to consider rural farmers' preferences for MSW compost qualities and access when designing their marketing strategies. Results of this study provide useful insights to compost business managers on the 'how', 'when', and 'where' to offer the input, such that rural farmers are attracted to buy. Attracting farmers to purchase compost means increased use of organic fertilizer and consequently improved soil health, crop yields; hence, incomes and food security. Specifically, the findings have implications for marketing waste-based compost produced by composting companies around cities in Ghana.

The study revealed that a key strategy for attracting rural farmers to MSW compost is to pelletize it, provide brand/label the bags and make the input available to the farmers in their communities. This tactic may have to be combined with significant price discounts at levels much lower than the current price. However, compost producers cannot combine significant price cuts with cost-recovery measures if they must remain in business for public benefit. Thus, the situation calls for much higher compost subsidies than the current offer through the national fertilizer subsidy program. Extra subsidies on organic over mineral fertilizers could offset the higher distribution costs (Folefack, 2008), which farmers presently are willing to pay less than the average.

Given the high average utility associated with not buying compost combined with very low literacy rates among the farmers, the importance of branding/labeling could be ostensive in that farmers, upon first sight, associate brands/labels to quality reputation. If so, branding/labeling becomes a useful marketing tool for initial purchase (uptake) decisions. However, farmers could also exploit it in avoiding subsequent purchases unless initial compost purchases prove valuable to them. Therefore, efforts should be made to improve the overall attractiveness through the other

attributes, especially pelletizing and delivery at villages. Educating farmers on the conservational values of compost should also be the long-term component of all MSW compost marketing

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Chapter 6

Conclusions and policy implication

Food insecurity and poverty continued to be major challenges for human development in Sub-Saharan Africa (SSA) due to low agricultural productivity linked to deteriorating soil conditions and inappropriate agrarian technologies. Though increasing mineral fertilizer application has always been the proposed remedy for resolving the crop yield crisis, the recent improvement in mineral fertilizer access in countries like Ghana has revealed that merely increasing mineral fertilizer does not resolve the farm yield crisis in African, where much of the farmlands are severely degraded. Meanwhile, organic fertilizers play a significant role in improving soil conditions for effective mineral fertilizer use. Thus, the focus on fertilizer use has shifted towards combining mineral with organic fertilizers for improved soil health and productivity. Towards this goal, agricultural development agencies in northern Ghana, for the past decade, have been priming farmers to access and use more organic fertilizers. However, the input remains minimally used in the area. This study contributes insights from farmers' perspectives to the growing literature on organic-inorganic fertilizer use debate in Sub-Saharan Africa by assessing farmers' decisions and behaviors regarding organic fertilizer use in northeastern Ghana.

First, the study explored farmer-decisions to identify trajectories (approaches) that farm-households follow to use organic fertilizer and related the identified approaches to farmers' socio-economic background. Second, considering the current needs of development agents to target beneficiaries for upscaling innovations, the study evaluated the behavioral costs (difficulty) of common organic practices (OFPs) and scaled farmers' general attitudes towards organic fertilizer use. Third, the study established the link between the input and household food security indexes (i.e., per capita food consumption and food gap), on the one hand, and farm labor use on the other, following the potential outcome framework. Finally, through a choice experiment, the study evaluated potential demand for commercial composts among rural farmers through willingness-to-pay.

6.1 Summary of empirical methods

The study employed various empirical methods, including exploratory factor analysis (EFA), seemingly unrelated regressions (SUR) analysis, explanatory Rasch model (ERM), endogeneous switching regression (ESR), endogeneous treatment-effect (ETE), Poisson regression, polynomial function, conditional multinomial logit (CML), mixed logit (MIXL), and generalized multinomial logit (G-MNL) to obtain results discussed in the different chapters.

In chapter 2, EFA classified organic fertilizer use decisions into unobservable but unique classes (approaches). After identifying the approaches, SUR established a relationship between each approach and farm/farmer characteristics while adjusting for inter-approach correlation. The SUR corrected biases in the coefficient on characteristic variables since OFM approaches were not entirely independent.

The ERM was used in chapter 3 as a scale that measures and maps OFPs' difficulty and farmer attitudes simultaneously, with a hybrid latent regression controlling for observed and unobserved farmer-groupings. It was appropriate to apply the ERM in scaling since farmer-grouping factors, including education level, risk behavior, organic fertilizer experience, livestock, farm resource ownership, and geographical location, influencing attitudes distorted the scale's objectivity and had to be controlled for. Controlling for scale distortions using farm/farmer factor variables also allows attitude levels to be explained.

Chapter 4 employed the ESR to estimate the effects of organic fertilizer on per capita food expenditure, food gap, and farm labor use. The model allowed identifying real determinants of organic fertilizer adoption and accounted for biases arising from endogeneity and self-selectivity caused by both observed and unobserved factors. This way, the model gave unobscured estimates of organic fertilizer effects. The ESR relies on linear function in continuous outcome variables. Through Box-cox functional form tests, the best linear transformations of the outcome variables were identified for the ESR model, but their untransformed values were also modeled using ETE and ETpoisson (for food gap) to check the robustness of estimates.

Chapter 5 employed the G-MNL framework on choice experiment data to estimate farmers' willingness-to-pay for critical municipal solid waste (MSW) compost attributes. The G-MNL model is very flexible in the specification, which was explored to identify and fit the best data generating process. It also allowed sources of preference heterogeneity among farmers to be identified and appropriately modeled on farmers' characteristics.

6.2 Summary of findings

In chapter 2, the EFA identified four approaches, which were named as Augmentary Compost Use Approach, Urban Human Waste Organic Fertilizer Approach, Integrated Livestock Manure Approach, and Mineral Fertilizer Cost Constraint Organic Approach. By the motivations and decisions characterizing them, the first three approaches are strategic in nature, while the last approach is borne out of necessity to provide soil nutrients under severe mineral fertilizer

constraints. The SUR analysis showed that different subsets of farmer characteristics characterized uptake of the approaches, but organic fertilizer management training is key to all.

The results in chapter 3 showed that an average organic fertilizer practice has a difficulty of 0.69 logits against average farmer attitude strength of -0.93 logits on the calibrated scale. The majority of the farmers (70%) have weak attitudes; hence, only three (19%) out of 16 OFPs matched average farmer's attitude strength, even though the OFPs, generally have moderate difficulty estimates. Latent regression revealed that attitude level strongly relates to socioeconomic factors, including higher education, resource ownership, and access to soil fertility management training. Participation in organic fertilizer policy and training programs is very critical to knowledge and skills acquisition and thus replaces education for the less-educated majority of the farmers.

The ESR analysis in chapter 4 revealed that observed and unobserved farmer-background factors determine both the farmers' decision to adopt organic fertilizer and the outcomes from adoption. On average, adoption is associated with an 11% increase in per capita food consumption and a 55% reduction in household food gap. Adoption, however, increases female labor use by 5.9 workdays (90%) and that of males by 1.3 workdays (9%), meaning nearly all (82%) of the increased labor burden is on female farmhands.

The empirical findings in chapter 5 showed that all the attributes studied are critical to MSW compost demand and farmers have widely varied preferences and willingness-to-pay for them, except the sales period. The variation is mainly due to unobserved randomness in preferences. However, farmer-background factors, including off-farm work participation, monthly household income, and ownership of means of transport, induce some scale variation among the farmers. On average, farmers are willing to pay GHs9.43 for a branded/labeled compost followed by GHs5.76, GHs4.49, and GHs2.49 for pelleted compost, delivery at the community, and for sales during a cash windfall, respectively. Farmers have GHs-33.36 disutility for deciding not to buy MSW compost, indicating that they may opt for their status quo fertilizer type if the MSW compost price exceeds GHs33.36.

6.3 Policy implications and recommendations

Several policy implications can be drawn from this study's findings, which show that rural farmers follow three main critical decision paths (management approaches) to obtain and use organic fertilizer, with reluctant attitudes though the input is beneficial to them. To the extent that organic fertilizer policy planning requires information on farmers' practices, the decision paths revealed by this study indicate useful path-dependencies that could be exploited to target farmers with

policies for increasing organic fertilizer adoption. Decision paths tend to be geographically location-specific within the study area.

Farmers showed weak attitudes toward organic fertilizer, but the weakness is conditioned by their socioeconomic background, such as low education. Since farmers' attitudes are strongly related to both education and access to soil fertility training, improving access to organic fertilizer training programs can replace formal education by equipping the less-educated majority with information, knowledge, and skills they need to use the input. Therefore a general policy for easing organic fertilizer adoption is to invest in training and extension programs that build average farmers' capacity to manage the input.

To draw-in non-adopters, there is a need to identify and mitigate unobserved factors opposing motivations to adopt organic fertilizer. The negative relationship between mineral and organic fertilizer use suggests a wrong notion about the inputs as being substitutes. Such a misconception, which hinders the effective use of the input, needs to be corrected. Therefore, sensitizing farmers on complementary roles of these inputs in sustainable crop production should be part of regular extension services.

Consistently, the results showed that farm equipment and other capital assets drive organic fertilizer adoption and its effects on adopters' welfare through food access and labor requirement. Labor supply could limit the adoption and intensity of organic fertilizer use. This calls for farm capital support programs to improve access to key farm equipment like tricycles and carts to ease organic fertilizer adoption and intensification among the farmers. Thus, providing female-user-friendly types of labor-saving farm equipment for collecting, transporting, and applying organic fertilizer is particularly recommended.

Farmers will buy commercial organic fertilizer if they can physically access it. Instead of relying entirely on on-farm production, which is usually inadequate, rural farmers could be encouraged to augment quantities of organic soil amendments they make with purchases from MSW compost dealers. The results of a discrete choice experiment suggest that reducing the purchase price, improving the qualities, and preferably making it available at the farmers' communities during times of cash windfalls can boost the use of purchased compost. This requires that the government subsidize MSW composts more than 50% subsidy, including transport costs, to enable compost dealers to distribute the input to rural areas.

Appendices

Appendix 1: Questionnaire



Christian-Albrechts University of Kiel, Germany
Institute of food economic and Consumer Studies

Socio-economic assessments of organic fertilizer use among smallholder farmers in Northern Ghana

Introduction

This is a study being conducted by the Department of Farm Management & Production Economics, Christian-Albrechts University of Kiel, in collaboration with UDS, to assess socio-economic implications of farmers' investments in Organic soil amendment practices. Please, note that the research is mainly academic, but stakeholders may use its finding for fertilizer policy planning. We shall keep all information given to us confidential. We, therefore, appeal to you to answer the following questions as candidly as possible. Thank you in advance for your cooperation.

Call back information

1. Community 2. Date3. Interviewer4. contact.....

Instructions

1. Where alternatives have been provided, circle the code number only.
2. Arrange alternatives in order of importance where you are required to rank.
3. For other questions, write your answers in the space provided.

Section A

Household and Plot Characteristics

a. Household characteristics:

- | | |
|--|------------------------|
| Aa/1. Sex of respondent | 1. Male 2. Female |
| Aa/2. Age of respondent (last birth date) | # Yrs<75 |
| Aa/3. What is the number of years spent in schooling? | # yrs<30 |
| Aa/4. Respondent's relationship to household head: 0. Self 1. Spouse, 2. Son/daughter, 3 others.
<i>If 0 (self), go to question number 8.</i> | |
| Aa/5. Gender of HH Head | 1. Male 2. Female |
| Aa/6. Age of HH Head (last birth date) | # Yrs<75 |
| Aa/7. What is the number of years spent in schooling by HH Head? | # yrs<30 |
| Aa/8. Years spent in school by the most educated member of HH | # |
| Aa/9. Number of people in the household | # |
| Aa/10. Number of Adults (>17 of age), | Females.... Males |
| Aa/11. Experience in crop farming | # yrs |
| Aa/12 The number of crops produced by household | # |

1. crop	2. Acreage
3.	4.
5.	6.
7.	8.
9.	10.
11.	12.

- | | |
|-------------------------------|--|
| Aa/13. Main occupation | 1. Farming 2. trading, 3 craft and artisanship 4. Formal job |
| Aa/14. Monthly HH expenditure | GHS |

Aa/15. Assets and their value in Ghana Cedis

Serial #	Which of the assets below do you have?	available		If yes, state the number available	Year of purchase	Cost of purchase	Income source for purchase
		yes	no				
Household Assets							
1	Mobil phone						
2	Radio						
3	Television						
4	Bicycle						
5	Motorcycle						
6	House						
Farm Assets							
7	Cutlass						
8	Hoe						
9	Knapsack						
10	Tricycle/minitruck						
11	Car/pickup						
12	Tractor						
13	Bullock set						
14	Donkey cart						
15	Soil ripper						
16	Hand planter						
17	Manure spreader						
Other assets, list them							

Aa/16. Total value of household assets

GHS

Aa/17. Total value farm assets

GHS

Aa/18. Other income sources

1. None 2. Off-farm income, 3. Transfers 4. both

b. Farm/Plot characteristic

Ab/1. What is the total area under cultivation of crops (Farm size)?

.....hectares,

Ab/2. What proportion crop farm is under cereal cultivation

.....hectares

Ab/3. Size of plot under organic soil amendment

.....hectare

Ab/4. Which of the crops is (are) grown using organic amendment?

1. Cereals
2. Legumes
3. Vegetables
4. Tubers
5. Mixed

Ab/5. Why do you use organic manure/compost for your crops?

.....

1. I thought it would be cheaper/profitable
2. I was convinced by NGO Officer
3. I was convinced by the government campaign
4. Market access through organic production
5. Other (specify)

.....

Ab/6. Specific cereal grown.

1. Maize
2. Millet
3. Sorghum
4. Mixed cropped

Ab/7. Rank the following Household farm objectives in order of importance to your household

1. food sufficiency,
 2. income/cash needs,
 3. cultural/ceremonial needs
 4. Intermediate input/ raw material
 5. Others, specify
- Ab/8. Indicate the Land tenure of your Plot
1. Own land,
 2. Communal
 3. Rented
- Ab/9. What is the rent value of your plot per farm season? GHS
- Ab/10. Plot distance from home, kilometers
- Ab/11. Rate the Depth of your farm topsoil as
1. Shallow
 2. Moderate
 3. Deep
- Ab/12. Rate the Soil quality as
1. Poor
 2. Good
- Ab/13. Rate Plot slop as
1. Steep
 2. Moderately sloping
 3. Flat
- Ab/14. How many years has the plot been under cultivation organic soil amendment

c. Resources, Governance and information limits/environmental and socio-economic shocks

- Ac/1. How many of the following livestock do you have
1. Cattle =*0.7
 2. Sheep =*0.1
 3. Goat =.....*0.1
 4. Pig =..... *0,2
 5. Fowls =*0.01
 6. Others,
- Ac/2. Have you sought credit OSA purpose (credit is needed but unable to obtain)? 1. yes 2. No
- Ac/3. Means of transport. 1. Non, 2. Bicycle 3. Motorbike 4. car
- Ac/4. Walking distance to village markets. # of km
- Ac/5. Walking distance to input markets # of km
- Ac/6. Have you benefited from any Government/NGOs policy for organic fertilization? 1. Yes. 2. No
- Ac/7. If yes, name it/them,,
- Ac/8. If yes, what support have you received?
1. Organic fertilizer subsidy
 2. Training on organic fertilizer preparation
 3. Training on organic soil amendment practices
 4. Plowing or ripping services
 5. Credit
 6. Certification of our farm produce
 7. Access to market for our produce
 8. Others,
- Ac/9. Do you still work with them? 1. yes 2. no
- Ac/10. How many farmer groups/FBOs does your household belong to? #.....
- Ac/11. Is any of the FBOs promoting organic fertilizer use? 1. yes 2. no
- Ac/12. If yes, name it.
- Ac/13. What exactly does the named FBO do to promote organic fertilizer use?
1. Organizes Training on compost/manure preparation
 2. Organizes Training on on-farm crop residue management
 3. Sources and supply manure/compost to members
 4. Others,
- Ac/14. How often do you meet?
1. Once a week
 2. Twice a month
 3. Once in a month

4. Once every quarter
- Ac/15. What is your Status in the farmer group?
1. executive member
 2. non-executive member
 3. old executive
 4. ordinary member
 5. other (specify)
- Ac/16. How many of the FBOs above are input/product marketing cooperatives? #.....
- Ac/17. How many Grain traders you know and trust to offer a fair price? #
- Ac/18. Frequency of Extension contact #/yr or season
- Ac/19. Rate quality of service, if any: 1. Very poor, 2. Poor, 3. Indifferent, 4. Good, 5. Very good
- Ac/20. Which of these shocks did your farm experience?
1. Pest and disease stress
 2. Waterlogging
 3. drought stress
- Ac/21. Is there any subsidy on organic inputs of your farm? 1. yes 2.no?
- Ac/22. How relevant is it to your decision to apply organic fertilizer on your farm? Rate: 0, 1, 2, 3, 4
0. very irrelevant,
 1. irrelevant
 2. do not know,
 3. Relevant.
 4. very relevant
- Ac/23. Is there any support in case of your crop failure? 1. yes 2. no
- Ac/24. How relevant is it in your decision to apply organic fertilizer on your farm? Rate: 0, 1, 2, 3, 4
0. very irrelevant,
 1. irrelevant
 2. do not know,
 3. Relevant.
 4. very relevant

Section B.

Production inputs, practices and outputs

- B/1. How many hectares is your maize/ cereal farm? # (ha)
- B/2. How much is the rent/ha per cropping season? GHS
- B/3. Describe your capital expenditure for the 2017 crop budget below:

Capital expenditure	Unit cost	Total
Ripping, Basins, plowing		
Tractor rental		
Bullock rental		
Hoe/basin used		
Spray equipment rental		
Transport rental (motorking)		
Others, specify		

- B/4. How many kilograms of manure/compost or sludge did you apply? #
- B/5. How much did a kilogram cost? #
- B/6. How many kilograms of chemical fertilizer did you apply? #
- B/7. How much did a kilogram cost #
- B/8. How many litres of weedicide were used on your farm for the activities below? #

Weeding activity	The quantity used (Itrs)	Unit cost	Total cost
1. Land clearing			
2. 1 st weeding			
3. 2 nd weeding			
4. 3 rd weeding			

- B/9. Which of the following type of seed did you use?
1. Farmer own seed Local Variety
 2. Farmer own Seed improved yield variety
 3. Farmer own seed Improved Drought resistant Variety
 4. Certified improved yield variety
 5. Certified improved drought resist. variety

B/10. How did you till your land?

1. Tractor plowing,
2. Bullock plow,
3. Hand plow,
4. Ripping,
5. Zero tillage

B/11. How much did it Cost to till the land?

.....GHS.

B/12. How many liters of pesticide did you use?

Litres, cost/ltr.....

B/13. How many man-days of labor was used for the following activities;

- | | |
|------------------------------------|------------------------------|
| 1. Land preparation, | # of male....., female |
| 2. Manure/ compost application | # of male....., female..... |
| 3. Chemical fertilizer application | # of male....., female..... |
| 4. Sowing, | # of male....., female |
| 5. Weeding | |
| 1. 1 st | # of male....., female |
| 2. 2 nd | # of male....., female |
| 3. 3 rd | # of male....., female |
| 6. Harvesting, | # of male....., female |
| 7. Transportation | # of male....., female |

B/14. What was the average wage for labor in 2017?GHS

B/15. Was the wage rate the same for males and females? (1=Yes, 2=No)

B/16. Why do you use a particular gender for your labor type? Choose applicable reason(s) below

A: Reason For Using Male Labour	B: Reason For Using Female Labour
1. They do the task well	1. They do the task well
2. It is a gender role (special skills)	2. It is gender role (special skills)
3. It was the cheapest available	3. It was the cheapest available
4. Other reasons, specify,.....	4. Other reasons, specify,.....

B/17. How much Fuel (in liters) was consumed on ;

- | | |
|------------------------------------|---------|
| 1. Land preparation, | #..... |
| 2. Manure/ compost application | # |
| 3. Chemical fertilizer application | # |
| 4. Sowing, | #..... |
| 5. Weeding, | # |
| 6. Harvesting, | #..... |
| 7. Transportation | #..... |

B/18. Maize/Cereal output quantity

of kgs.....

Output Type	Number of 80kg bags	price/bag	Total value
Gross output			
Output consumed			
Output as gift			
Output sold			
Other outputs	1. 2. 3.	1., 2., 3...	1..., 2..., 3....

Section C

Affective Evaluation Statements

Instructions:

1. Answer 'yes' if applicable, otherwise 'no' to each of the statements below concerning organic fertilizer use.
2. If 'yes', rate yourself on how successful you perform on the scale provided. (1 = below average, 2= average 3= above average, 4 = excellent)

C/1. I have received training (including demonstrations, informal training) away from my farm site on soil fertility management.

- 1 = no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/2. I identify and incorporate into the soil crop residues that are high in nutrients and easy to decompose.
1 = no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/3. I collect crop residues from my neighbors after harvesting, which I add to those I produce from my farm to have enough.
1 = no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/4. Some times I apply crop residues as mulch on my farm
1 = no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/5. I practice crop rotation/intercropping because it fits with my cropping patterns.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/6. I always include legumes in the crop rotation/intercropping.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/7. I keep livestock/poultry so that I can get manure to apply on my farm.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/8. I collect animal manure from neighboring farms (max 1/2 km) to obtain sufficient manure for my crops.
1 = no, 2= yes if yes, rate (1, 2, 3 or 4)
- C/9. I have to travel for several kilometers (more than 3 km) to get livestock manure.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/10. Have to contract Fulani herdsmen to kraal their cattle on my plot for several weeks, some months before cropping.
1 = no, 2= yes if yes, rate (1, 2, 3 or 4)
- C/11. I secure manure/ compost from community Kraal.
1 = no, 2= yes if yes, rate (1, 2, 3 or 4)
- C/12. I have to hire a donkey cart from my neighbor to transport livestock manure from the source (more than 3 km) to my farm.
1 = no, 2= yes if yes, rate (1, 2, 3 or 4)
- C/13. I arrange with my neighbors who keep livestock to supply me with livestock manure.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/14. I often apply agro by-products from nearby agro-processing factories on my farm to supplement livestock manure and mineral fertilizer.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/15. I use straw/crop residues in the livestock house for bedding and to absorb urine, and I later apply the bedding in the field (own livestock/do not own livestock).
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/16. I have paved the livestock house floor to ease the collection of manure.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/17. I have enough family labor to assist in the collection and application of organic fertilizer.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/18. I hire enough labor to assist in the application of livestock manure.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/19. I easily mobilize my neighbors and friends to help me in applying livestock manure to my crops.
1 = no, 2= yes if yes, rate (1, 2, 3 or 4)
- C/20. I spread fresh livestock manure on the surface of the soil.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/21. I compost livestock manure before spreading it on the soil surface.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/22. I incorporate manure into the soil any time I apply.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/23. I apply mineral fertilizers in micro-doses to crops.
1 = no, 2= yes if yes, rate (1, 2, 3 or 4)
- C/24. I must combine mineral fertilizers with organic manure because they have different roles.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/25. If I have enough chemical fertilizer, I will not apply manure or compost.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)
- C/26. I know that without organic fertilizer, chemical fertilizer does not work well.
1= no, 2= yes if yes, rate (1, 2, 3, or 4)

A: Farm input Purchasing and application behavior

The first sets of questions are about your actual food purchasing and consumption practices. Please remember that your answers are completely confidential, and we are interested in what you really do and not what you think you should do.		
D/1	Do you do the shopping for inputs for your farm?	1. Yes, 2. No
D/2	Where do you usually purchase most of your food?	1. Open market 2. Supermarket 3. Directly from the manufacturers 4. Home delivery 6. Agrochemical Specialist store
D/3	Do you read product labels before purchase?	1. Yes, 2. No
D/4	How often do you compost your household waste products like food scraps at home?	1 Always 2. Most of the time 3. Occasionally 4. Never

The next sets of questions are about the sorts of things that influence your decisions about farm inputs. We would like you to give each item a score out of five (5), depending on how important it is to you when you decide what input you will use. A score of 1 = "item is not at all important," and 5 = "item is extremely important".When answering, it is important that you let us know which item influences your decisions on what you eat, but not how much you think they should influence your decisions.					
D/5	How important is it to you that the food you eat on a typical day is:				
	completely not important	not important	neutral	moderately important	extremely important
Your religion does not forbid it.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
It has no blemishes/ visible defects.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
It is quick (easy) to use.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Readily available in agrochemical shops/markets.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
It is familiar/ Is what you usually eat.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
It conforms to what is encouraged in the community.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Experts recommend it.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
It Is not expensive (cheap).	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Comes from a country that you approve of politically.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
It is grown manufactured in Ghana.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Its use conserves the environment.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
D/6	How strongly do you agree or disagree with each of the following statements?				
	Completely agree	agree	Neutral	disagree	Completely disagree
Environmental problems are highly exaggerated	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
The importance of organic fertilizer to crop production is overstressed.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
My actions are too small to affect any environmental quality.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
The government is doing enough to encourage organic fertilizer use.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
I think it is fair to pay farmers more for producing food in an environmental-friendly way.	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

D/7	If you were to receive more organic fertilizer(compost) information, which medium would be the best for you?	1. Neighbours <input type="checkbox"/> 2. Relatives <input type="checkbox"/> 3. Friends 4. Extension agents <input type="checkbox"/> 5. Religious/traditional leaders <input type="checkbox"/> 6. Radio <input type="checkbox"/> 7. Television <input type="checkbox"/> 8. Public meetings <input type="checkbox"/> 9. Agricultural shows <input type="checkbox"/> 10. Others
D/8	Are you aware of commercial compost for sale?	1. Yes, 2. No
D/9	If yes, when did you know or become aware of the input? (Years)
D/10	If you were to plan for buying compost for your maize farm, when and where will you like to have it?	When..... at i. after selling preceding crop input shop ii. when it is time for plow.... Home/comm.
D/11	How would you best describe a compost?

In questions D/12-D/14, there are different combinations of profiles for compost sold. Alternative A and B are MSW compost bags, while alternative C is an opt-out. Please, which bag would you buy given the attributes?

D/12			
Attribute	Compost bag A	Compost bag B	Opt-Out C
Form	 Unpelleted compost	 Pelleted compost	If alternative A & B are the only options available to me, I will not buy MSW compost
Label	 Branded/labeled bag	 Unbranded/unlabeled bag	
Period of Sales	 At planting time	 At preceding crop harvest	
Delivery Point	 Delivered at community	 Delivered nearest input shop	
Price	GHS 35	GHS 25	
Choose	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	Will not buy <input type="checkbox"/>

D/13			
Attribute	Compost bag A	Compost bag B	Opt-Out C
Form	 <p>Pelleted compost</p>	 <p>Unpelleted compost</p>	<p>If alternative A & B are the only options available to me, I will not buy MSW compost</p>
Brand/Label	 <p>Unbranded/unlabeled bag</p>	 <p>Branded/labeled bag</p>	
Period of Sales	 <p>At preceding crop harvest</p>	 <p>At planting time</p>	
Delivery Point	 <p>Delivered nearest input shop</p>	 <p>Delivered at community</p>	
Price	GHS 15	GHS 25	
Choose	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	Will not buy <input type="checkbox"/>

D/14			
Attribute	Compost bag A	Compost bag B	Opt-Out C
Form	 <p>Pelleted compost</p>	 <p>Unpelleted compost</p>	<p>If alternative A & B are the only options available to me, I will not buy MSW compost</p>
Brand/Label	 <p>Unbranded/unlabeled bag</p>	 <p>Branded/labeled bag</p>	
Period of Sales	 <p>At planting time</p>	 <p>At preceding crop harvest</p>	
Delivery Point	 <p>Delivered at community</p>	 <p>Delivered nearest input shop</p>	
Price	GHS 35	GHS 15	
Choose	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	

D/15			
Attribute	Compost bag A	Compost bag B	Opt-Out C
Form	 Unpelleted compost	 Pelleted compost	If alternative A & B are the only options available to me, I will not buy MSW compost
Brand/Label	 Unbranded/unlabeled bag	 Branded/labeled bag	
Period of Sales	 At preceding crop harvest	 At planting time	
Delivery Point	 Delivered at community	 Delivered nearest input shop	
Price	GHS 25	GHS 15	
Choose	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	Will not buy <input type="checkbox"/>

D/16			
Attribute	Compost bag A	Compost bag B	Opt-Out C
Form	 <p>Unpelleted compost</p>	 <p>Pelleted compost</p>	<p>If alternative A & B are the only options available to me, I will not buy MSW compost</p>
Brand/Label	 <p>Branded/labeled bag</p>	 <p>Unbranded/unlabeled bag</p>	
Period of Sales	 <p>At preceding crop harvest</p>	 <p>At planting time</p>	
Delivery Point	 <p>Delivered nearest input shop</p>	 <p>Delivered at community</p>	
Price	GHS 15	GHS 35	
Choose	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	Will not buy <input type="checkbox"/>

D/17			
Attributes	Compost bag A	Compost bag B	Opt-Out C
Form	 <p>Pelleted compost</p>	 <p>Unpelleted compost</p>	If alternative A & B are the only options available to me, I will not buy MSW compost
Brand/Label	 <p>Branded/labeled bag</p>	 <p>Unbranded/unlabeled bag</p>	
Period of Sales	 <p>At planting time</p>	 <p>At preceding crop harvest</p>	
Delivery Point	 <p>Delivered nearest input shop</p>	 <p>Delivered at community</p>	
Price	GHS 25	GHS 35	
Choose	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	Will not buy <input type="checkbox"/>

D/18			
attribute	Compost bag A	Compost bag B	Opt-Out C
Form	 <p>Pelleted compost</p>	 <p>Unpelleted compost</p>	<p>If alternative A & B are the only options available to me, I will not buy MSW compost</p>
Brand/Label	 <p>Unbranded/unlabeled bag</p>	 <p>Branded/labeled bag</p>	
Period of Sales	 <p>At planting time</p>	 <p>At preceding crop harvest</p>	
Delivery Point	 <p>Delivered at community</p>	 <p>Delivered nearest input shop</p>	
Price	GHS 35	GHS 25	
Choose	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	

D/19			
Attribute	Compost bag A	Compost bag B	Opt-Out C
Form	 Unpelleted compost	 Pelleted compost	If alternative A & B are the only options available to me, I will not buy MSW compost
Brand/Label	 Branded/labeled bag	 Unbranded/unlabeled bag	
Period of Sales	 At preceding crop harvest	 At planting time	
Delivery Point	 Delivered nearest input shop	 Delivered at community	
Price	GHS 15	GHS 25	
Choose	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	Will not buy <input type="checkbox"/>

D/20			
Attribute	Compost bag A	Compost bag B	Opt-Out C
Form	 Unpelleted compost	 Pelleted compost	If alternative A & B are the only options available to me, I will not buy MSW compost
Brand/Label	 Unbranded/unlabeled bag	 Branded/labeled bag	
Period of Sales	 At planting time	 At preceding crop harvest	
Delivery Point	 Delivered nearest input shop	 Delivered at community	
Price	GHS 35	GHS15	
Choose	I will buy <input type="checkbox"/>	I will buy <input type="checkbox"/>	Will not buy <input type="checkbox"/>

Appendix 2: Curriculum Vitae

Personal Information

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Academic And Professional Qualification

2017-2020 Ph.D. student at the Department of Farm Management and Production Economics, University of Kiel, Kiel, Germany
2009-2011 M.Phil.(M.Sc) Agribusiness at University of Ghana, Legon, Accra
2003-2007 B.Sc Agric. Technology at University for Development Studies, Tamale, Ghana
1997-2000 Teachers' Certificate "A" (Post-Sec.) UCC, Gbewa College, Pusiga, Ghana
1994-1996 SSSCE at Navrongo Secondary School, Navrongo, Ghana

Awards: Ghanaian-German Postgraduate Training Program Scholarship at the University of Kiel, Germany
Netherlands Fellowship Program (NUFIC) Scholarship award to Wageningen UR for Local Economic Development (LED) Course. October 2014

African Agricultural Technology Fund (AATF) Sponsorship to the 18th Annual Conference of International Consortium on Applied Bio-economy Research (ICABR) at Nairobi, Kenya, June 2014

Membership of Learned Societies

Agricultural and Applied Economics Association (AAEA), America
International Society for Development and Sustainability (ISDS), Japan
International Consortium on Applied Bio-economy Research (ICABR), Italy

Work Experience

Lecturer, University for Development Studies, Nyankpala Campus, FAAE-CCFS (2015-2017),
Asst. Lecturer, University for Development Studies, Nyankpala Campus, FACS –CCFS (2013-2015)
Zonal Supervisor, WIENCO Ghana Ltd, Masara N'Arziki Farmers Association, Damango and Chereponi, Ghana (2011 – 2013)
Agriculture Master, Ghana Education Service, Tiyumba Junior High School, Tamale, Ghana (2007 – 2009)
Teacher, Ghana Education Service, Abrubruwa DA Primary School, Nkwanta, Ghana (2000-2007)

Publications

Daadi BE, and Latacz-Lohmann U (2020). Organic fertilizer use by smallholder farmers: typology of management approaches in northern Ghana. *Renewable Agriculture and Food Systems* 1–15. <https://doi.org/10.1017/S1742170520000228>

Abugri, Stephen A., Joseph Amikuzuno and **Edward B. Daadi** (2017). Looking out for a better mitigation strategy: Smallholder Farmers' Willingness-to-pay for Drought-Index Crop Insurance Premium in the Northern Region of Ghana. *Agric & Food Secur* (2017) 6:71. <https://doi.org/10.1186/s40066-017-0152-2>

Issahaku Gazali, **Daadi B. E.** and Seini A-Rahman Y. (2016). Evaluating Agricultural Policy Impacts in Ghana: The Case of Food Crop Development Project in Ejura-Sekyedumase *Journal of Poverty, Investment and Development*, (28):10-16. ISSN 2422-846 www.iiste.org

Daadi, B.E., Issahaku, and G. & Amikuzuno, J. (2015). An Assessment of Allocative Efficiency of Organic Mango Farms in Northern Ghana. *Archives of Business Research*, 3(2), 114-124. <https://doi.org/10.14738/abr.32.991>

Daadi B. E., Issahaka G. and Amikuzuno J. (2014). “Technical Efficiency Analysis of Organic Mango Out-grower Farm Management Types: The Case of Integrated Tamale Fruit Company (ITFC) in Northern Region” *African Journal of Agricultural Economics and Rural Development* 2 (3), 129-137.

Amikuzuno J., G. Issahaku and **E. B. Daadi** (2013). Price Transmission between Imported and Local Rice Markets in a Liberalized Economy: Are Ghana’s Rice Wars Just Much I Do about Nothing? *Journal of Economics and Sustainable Development*, 4(20), 109-11. <http://iiste.org/Journals/index.php/JEDS/article/view/9816/10021>

Language proficiency: English, Moar, Twi, Ewe, Deutsch
Computer competencies: Stata; SPSS; Frontier 4

Eidesstattliche Erklärung gem. §11 Absatz 2 (5)

Hiermit erkläre ich an Eides statt, dass ich die vorgelegte Dissertation mit dem Titel „ Socioeconomic Assessments of Organic Fertilizer Use Among Smallholder Farmers in Northern Ghana

“ selbständig und ohne unerlaubte Hilfe angefertigt habe

Kiel, den 09.11.2020

Unterschrift



Erklärung gem. §11 Absatz 2 (6)

Hiermit erkläre ich, dass ich die vorgelegte Dissertation mit dem Titel „ Socioeconomic Assessments of Organic Fertilizer Use Among Smallholder Farmers in Northern Ghana

“noch keinem anderen Fachbereich bzw. noch keiner anderen Fakultät vorgelegt habe.

Kiel, den 09.11.2020

Unterschrift



Erklärung gem. §11 Absatz 2 (7)

Hiermit erkläre ich, dass die vorgelegte Dissertation nach den Regeln guter wissenschaftlicher Praxis (Standard wissenschaftlichen Arbeitens nach den Empfehlungen der DFG) abgefasst wurde.

Kiel, den 09.11.2020

Unterschrift



Declaration

M.Sc. Bunborn Edward Daadi

Statutory Declaration:

Herewith I declare on oath that I am not subject to any pending case of public prosecution.

Kiel, 10. 11. 2020

Signature 

Anlage 3

C A U	Christian-Albrechts-Universität zu Kiel	Agrar- und Ernährungs- wissenschaftliche Fakultät
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Declaration of co-authorship

If a dissertation is based on already published or submitted co-authored articles, a declaration from each of the authors regarding the part of the work done by the doctoral candidate must be enclosed when submitting the dissertation.

1. Doctoral candidate

Name: **Daadi, Bunbom Edward**

2. This co-author declaration applies to the following article:

Organic fertilizer use by smallholder farmers: typology of management approaches in Northern Ghana

The extent of the doctoral candidate's contribution to the article is assessed on the following scale:

- A. Has contributed to the work (0-33%)
- B. Has made a substantial contribution (34-66%)
- C. Did the majority of the work independently (67-100%)

3. Declaration on the individual phases of the scientific work (A,B,C)

Extent

Concept: Formulation of the basic scientific problem based on theoretical questions which require clarification, including a summary of the general questions which, it is assumed, will be answerable via analyses or concrete experiments/investigations	C
Planning: Planning of experiments/analyses and formulation of investigative methodology, including choice of method and independent methodological development, in such a way that the scientific questions asked can be expected to be answered	C
Execution: Involvement in the analysis or the concrete experiments/investigation	C
Manuscript preparation: Presentation, interpretation and discussion of the results obtained in article form	C

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10.11.2020	Uwe Latanz-Lohmann	<i>U. Latanz-Lohmann</i>

Anlage 3

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Organic fertilizer practices and Farmers' attitude in Northern Ghana: empirical insights using the attitude-as-behavior model

The extent of the doctoral candidate's contribution to the article is assessed on the following scale:

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- B. Has made a substantial contribution (34-66%)
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Name: **Daadi, Bunbom Edward**

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Organic Fertilizer Adoption, Household Food Access, and Gender-based Farm Labor Use: Evidence from Northern Ghana

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Execution: Involvement in the analysis or the concrete experiments/investigation	c
Manuscript preparation: Presentation, interpretation and discussion of the results obtained in article form	c

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C A U	Christian-Albrechts-Universität zu Kiel	Agrar- und Ernährungs- wissenschaftliche Fakultät
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Declaration of co-authorship

If a dissertation is based on already published or submitted co-authored articles, a declaration from each of the authors regarding the part of the work done by the doctoral candidate must be enclosed when submitting the dissertation.

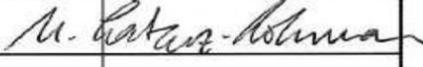
1. Doctoral candidate	
Name:	Daadi, Bunbom Edward

2. This co-author declaration applies to the following article:	
Finding market for municipal solid waste compost in Northern Ghana: rural farmers' willingness to pay for essential attributes	

The extent of the doctoral candidate's contribution to the article is assessed on the following scale:

- A. Has contributed to the work (0-33%)
- B. Has made a substantial contribution (34-66%)
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