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ECONOMICS OF COCOA EXTENSION SERVICE QUALITY, CLIMATE SMART ADAPTATION AND EFFICIENCY OF PRODUCTION NEXUS: IMPLICATION FOR FOOD SECURITY IN GHANA

EMMANUEL WISGTOS INKOOM

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ECONOMICS OF COCOA EXTENSION SERVICE QUALITY, CLIMATE SMART ADAPTATION, AND EFFICIENCY OF PRODUCTION NEXUS: IMPLICATION FOR FOOD SECURITY AMONG COCOA FARMERS IN GHANA

BY

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SEPTEMBER 2020

DECLARATION

Candidate's Declaration

I hereby declare that this thesis is the result of my own original research and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature ………………………. Date ………………………………

Name: Emmanuel Wisgtos Inkoom …………………………………………………………

Supervisors' Declaration

We hereby declare that the preparation and presentation of the thesis were supervised in accordance with the guidelines on supervision of thesis laid down by the University of Cape Coast.

Principal Supervisor's Signature ……………………… Date ………………

Name: Prof. Henry DeGraft Acquah ……………………………………………………

Co-Supervisor's Signature …………………………… Date ………………

Name: Dr. Samuel Kwasi Ndzebah Dadzie ……………………………………………...

ABSTRACT

The increasing consequences of climate change and persistent low farm-level productivity on the livelihood security of cocoa farmers have become a growing concern, thereby calling for empirical research findings to support appropriate policy direction. Given this, the current study examined the food security implication of the economics of cocoa extension service quality, climate-smart adaptation, and efficiency of production nexus. A multistage sampling approach was used to randomly select seven hundred and twenty cocoa farmers from across the cocoa regions. In analysing the empirical data collected from the sampled farmers, the study utilised a mixture of descriptive statistics and econometrics models including service quality measurement model, mixed logit model, multivariate probit model, stochastic frontier model, the Heckit treatment effect model and the structural equation model. The result of the analysis showed that perceived increase in extension service quality positively influences farmers' willingness to pay for climate smart cocoa extension service. It was additionally observed that farmers' choice of climate smart adaptation practices was significantly explained by their perception of climate variability and change effect. The study noted that most farmers exhibited significant levels of inefficiencies and were also marginally food secured. It was empirically confirmed that improvement in the quality of extension service delivery to farmers significantly increases their adoptions of climate smart adaptations choices which was also found to positively influence the production efficiencies of farmers. In addition, the study empirically found out that farmers' food security situation can significantly be improved as their efficiencies in production increases. Thus, improving cocoa extension service quality by making its climate smart is critical and must be given serious attention in national policy directions by policymakers seeking to improve cocoa productivity/production and for that matter livelihood security of cocoa farmers.

KEY WORDS

Cocoa Farmers

Climate Smart Adaptation

Extension Service Quality

Efficiency of Production

Food Security

Preference and willingness to pay

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I also wish to thank my family and friends for their support, especially, my wife, Felicia Assan Inkoom, my father, Samuel Inkoom and my mother, Cecilia Abbam Inkoom.

DEDICATION

To my wife and children: Felicia Assan Inkoom, Emmanuel Wisgtos Glory Inkoom and Emmanuella Wisgtos Miracle Inkoom.

TABLE OF CONTENTS

LISTS OF TABLES

LISTS OF FIGURES

LIST OF ACRONYMS

ACSCES	Advanced Climate Smart Cocoa Extension Service
AE	Allocative Efficiency
COCOBOD	Ghana Cocoa Board
CSCES	Climate Smart Cocoa Extension Service
CSA	Climate Smart Adaptation
DCE	Discrete Choice Experiment
EE	Economic Efficiency
FAO	Food and Agricultural Organisation
HFS index	Unidimensional household food security index
MHFS index	Multidimensional household food security index
HFIV index	Unidimensional Household food insecurity vulnerability index
MHFIV index	Multidimensional household food insecurity vulnerability index
IPCC	Inter-Governmental Panel on Climate Change
MoFA	Ministry of Food and Agriculture
TCES	Traditional Cocoa Extension Service
TE	Technical Efficiency
SDGs	Sustainable Development Goals
PLS-SEM	Partial Least Square Structural Equation Model
SERVPER model	Service Quality Performance Measurement Model
WTP	Willingness to pay

CHAPTER ONE

INTRODUCTION

This chapter discusses the background to the study, the research problem, research objectives, and questions. The chapter further presents the research hypotheses, significance of the study, delimitation, and limitation of the study. The chapter makes a case for the rationale for undertaking this study.

1.1 Background to the Study

In the Ghanaian economy, cocoa is an important economic crop that generates about $2 billion in foreign exchange annually and employs about 800,000 farm families (Ghana Cocoa Board [COCOBOD], 2019). Although the sector has chalked many successes over the years, the performance of the sector has come under threat due to climate change effect (including climate variability and extremes) in recent times (Wiah & Twumasi-Ankrah, 2017; Denkyirah, Okoffo, Adu, & Bosompem, 2017; Okoffo, Denkyirah, Adu, & Fosu-Mensah, 2016; Forest Trends, 2013). Again, despite the significant government investment in the sector, it has been observed that the sector continues to exhibit persistent low farm-level productivity over the years. For instance, available data shows that the average farm-level productivity in Ghana is about 400kg/ha compared to the potential optimum of 1.5tons/ha, and this is considered as one of the lowest in the world (World Cocoa Foundation, 2019; COCOBOD, 2019; COCOBOD & Forest Initiative, 2017). This suggests that the average cocoa farmer loses about 73 percent of his/her annual potential yield as a result of the persistent low farm-level productivity and climate change effects.

In addition, other studies have reported a significant decline in farm income and food security status among cocoa farming households as a result of the low productivity (Wiah & Twumasi-Ankrah, 2017; Schouten, 2016; Hutchins, Tamargo, Bailey, & Kim, 2015; Codjoe, Ocansey, Boateng, & Ofori, 2013; Forest Trends, 2013). Drawing from the observed average productivity records, it can be extrapolated that the average farm-level income is about GH¢ 3,040/ha which is far below the potential optimum of GH¢ 11,400/ha. This shows that the average cocoa farmer loses about 73 percent of his/her annual potential income as a result of the low farm-level productivity. The observed situation has directed attention to climate change and productivity improvement actions. Climate change as a concept refers to a statistically significant variation in either the mean state of the climate or in its variability, persisting for an extended period (typically decades or longer) (Intergovernmental Panel on Climate Change [IPCC], 2014).

In recognition of the devastating impact of climate change, it was observed that the cocoa sector needs to shift from the predominant expansionist production system to climate smart system by mainstreaming climate smart adaptation technologies in the current production system (COCOBOD & Forest Initiative, 2017; Denkyirah *et al*., 2017; Ministry of Food and Agriculture [MoFA], 2015; Forest Trends, 2013). Climate smart adaptation as a concept refers to the adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities (IPCC, 2014, 2007). In the agricultural landscape, climate smart adaptation as a technological response seeks to position farmers in achieving higher productivity growth and livelihood security enhancement in the face of climate change by building their resilience and adaptive capacity (IPCC, 2014; COCOBOD & Forest Initiative, 2017; MoFA, 2015; Forest Trends, 2013). It can however be asserted that for any agriculture-related technology (i.e., climate smart adaptation technologies) to yield its intended policy objective of productivity growth and livelihood security enhancement, the role of quality extension service delivery and farm-level efficiency of production cannot be overlooked (COCOBOD & Forests Initiative, 2017; Inkoom & Micah, 2017; Asare, 2014; Forest Trend, 2013).

This assertion is anchored on the World Bank's definition of agricultural extension service, which defines agricultural extension service as the process that helps farmers become aware of improved technologies and adopt them in order to improve their efficiency, income, and welfare (Purcell & Anderson, 1997). From the definition, it can be deduced that improving the quality of extension service has implication for increasing technology adoption with a sequential impact on productivity (efficiency of production) and livelihood security (especially food security situations). This is because in following the literature, it can be argued that for extension service delivery to yield optimum result, the issue is not about quantity, but rather the quality of the service (Elias, Nohmi, Yasunobu, & Ishida, 2016; Abdel-Ghany & Diab, 2015). Service quality as a concept, therefore, defines the ability of a service provider to meet or exceed consumers' expectations, by addressing the discrepancy between consumer expectations and service performance (Datta & Vardhan, 2017; Ali & Raza, 2017; Oh & Kim, 2017). The quality of extension service delivery can, therefore, be said to impact the service utility derived by farmers which have implication for the adoption of climate smart adaptation technologies that are introduced to the farmers. Given the current trends of the increasing consequences of climate change, improving extension service quality by making it climate smart is critical in understanding the adaptation decisions of cocoa farmers. However, the development and provision of an improved extension service (i.e., climate smart cocoa extension service) comes with an additional cost that cannot be shouldered alone by the government given the declining budget space. This raises the issue of cost-sharing arrangement;

requiring an empirical understanding of farmers' preference and willingness to pay for improved extension service.

Another important question that arises is whether higher adoption of climate smart adaptation measures through the provision of quality extension service alone is sufficient to translate into higher levels of productivity growth. The answer obviously is no. This is because, both theoretical and empirical literature has shown that the productivity impact of technology adoption is dependent on the efficient application of the technology given the available resources (Bogetoft & Otto, 2019; Henningsen, 2019; O'Donnell, 2018, Inkoom & Micah, 2017; Behr, 2015). Thus, the best way to access productivity improvement is through efficiency estimation, which for this study purposed is indicated by economic efficiency. Economic efficiency as a concept refers to the ability of farm units to obtain maximum output with minimum inputs, given input prices at the existing technology (Inkoom & Micah, 2017; Coelli, Prasada RAO, O'Donnell & Battese, 2005; Farrell, 1957).

Additionally, economic efficiency analysis points out the radial deviation from the optimum frontier and the possible factors that account for the deviations from the frontier. This, therefore, suggests that the measurement of economic efficiency (which captures both technical and allocative efficiencies) is key to understanding how to generate higher productivity growth in cocoa production and for that matter the livelihoods security enhancement of farmers (which in this study context is measured by their food security situation). Stemming from the above arguments, and in the face of the increasing climate change (including climate variability and extremes) and its distressing effect on agricultural productivity and food security; this study is of the firm belief that an empirical knowledge on the connects between extension service quality, climate smart adaptation, and efficiency of production is relevant for national policies seeking to improve the livelihood security of cocoa farmers.

1.2 Statement of the Problem

Globally, Ghana is the second largest producer of cocoa beans, holding an enviable record of producing the best premium cocoa bean with an attractive premium price, which is expected to translate into better livelihood security of cocoa farmers (World Cocoa Foundation, 2019; COCOBOD, 2019). Unfortunately, the successful transmission of this competitive advantage in the livelihood security enhancement of cocoa farmers over the years has been heavily challenged due to adverse consequences of climate change and persistent low farm-level productivity (COCOBOD & Forest Initiative 2017; Okoffo *et al*., 2016; Obeng & Adu, 2016; Owusu & Frimpong, 2014; Onumah, Al-Hassan, & Onumah, 2013; Forest Trends, 2013; Aneani *et al*., 2011). Evidence shows that the adverse consequence of climate change effect couple with the observed persistent low farm-level productivity has impacted negatively on the livelihood security of cocoa farming households, for example, their food security situation (COCOBOD & Forests Initiative, 2017; Wiah & Twumasi-Ankrah, 2017; Kuwornu, Suleyman, & Amegashie, 2013; Owusu & Frimpong, 2014; Asamoah, Owusu Ansah, Anchirinah, Aneani, & Agyapong, 2013).

As an effort to address the livelihood security impact of the adverse consequence of climate change and persistent low farm-level productivity, the government acting through COCOBOD initiated the productivity enhancement and climate smart cocoa production programmes to sustainably increase productivity, resilience (adaptation), and achievement of national food security and development goals (COCOBOD & Forests Initiative, 2017; McKinley, Asare, & Nalley, 2015; Forest Trend, 2013). A review of the productivity enhancement and climate smart cocoa production programme frameworks identifies certain key gaps that when filled, are critical as the pragmatic solution root to the livelihood security impact of the adverse consequences of climate change and persistent low farm-level productivity. These key gaps can be summarised around three main elements or support mechanisms as illustrated in Figure 1.1 (COCOBOD & Forests Initiative, 2017; Forest Trends, 2013). That is, the role of quality extension service delivery, efficiency of production and mainstreaming of climate smart adaptation technologies or practices in the cocoa value change.

A look at the figure shows that one could pick on any of the support mechanisms as the solution root to address the problem. However, connecting this to the World Bank's definition of agricultural extension service brings to light the significant connects between these three elements. As such, a holistic approach to assessing the implication of the nexus between them is critical in addressing the livelihood security impact of the adverse consequence of climate change and persistent low farm-level productivity on cocoa farmers. Unfortunately, existing literature that has attempted to investigate the implications of these three important elements has mostly followed a unilateral approach rather than a multilateral approach covering the interactive effect of all three elements (Denkyirah *et al*., 2017; Ehiakpor, Danso-Abbeam, & Baah, 2016; Hutchins *et al*., 2015; McKinley *et al*., 2015; Asante & Amuakwa-Mensah, 2014; Onumah, Al-Hassan, & Onumah, 2013; Aneani *et al*., 2011). This consequently limits their overall policy implication in addressing the issue of adverse consequences of climate change effect and persistent low farm-level productivity on the livelihood security of cocoa farmers in Ghana.

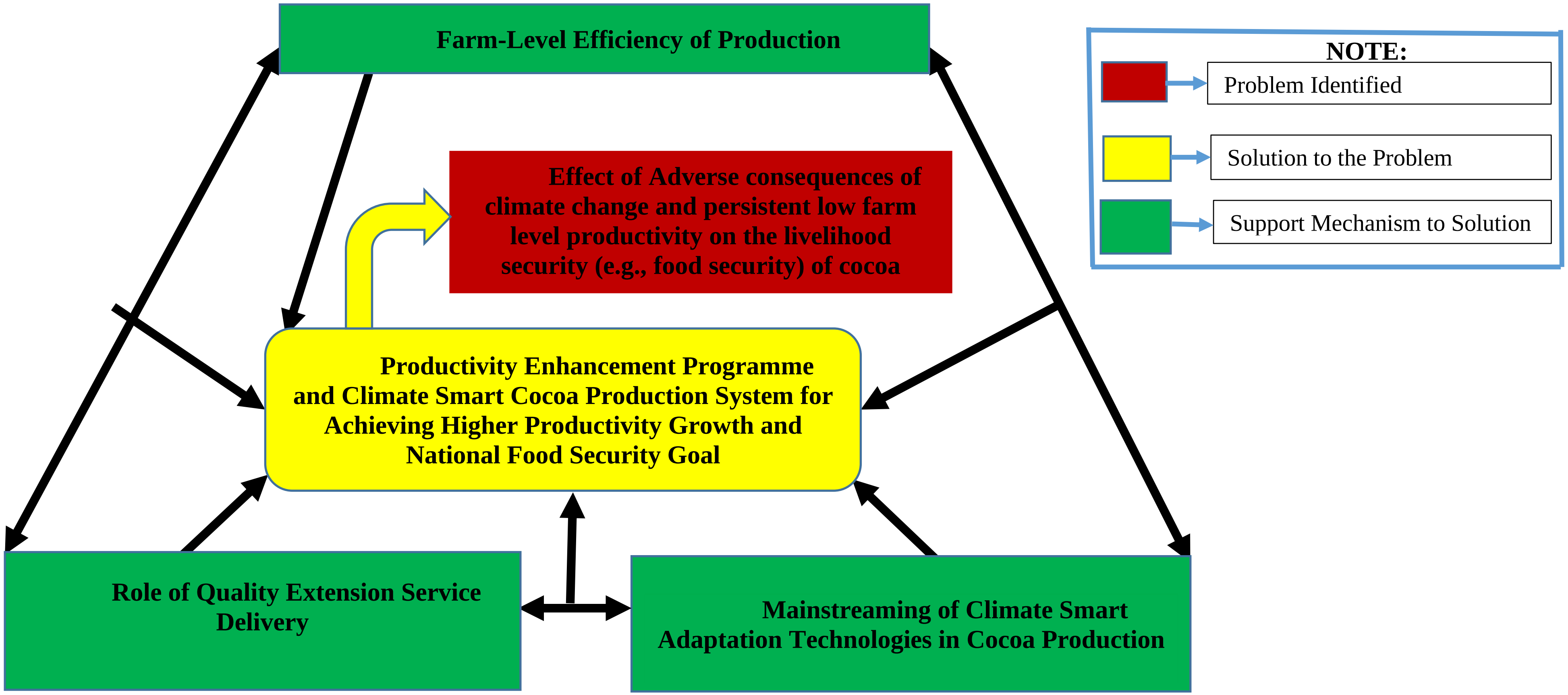


Figure 1.1: **Schematic Diagram of the Problem Identified and its Solution Roots**
Source: Authors constructs, Inkoom (2019)

For instance, in addressing the gaps associated with the role of quality extension service delivery, some studies have suggested that extension service providers must adopt effective and efficient approaches to disseminate technological products to cocoa farmers towards crop productivity improvements (Danso-Abbeam, Ehiakpor, & Aidoo, 2018; Altalb, Filipek, & Skowron, 2015; Nana, Asuming-Brempong, & Nantui, 2013). However, a review of service evaluation literature shows that the effectiveness and efficiency of any service delivery must reflect in the quality of service delivered and this when situated within the context of utility maximisation is critical in influencing farmers' climate smart adaptation choices (Datta & Vardhan, 2017; Ali & Raza, 2017; Oh & Kim, 2017; Elias *et al.*, 2016; Abdel-Ghany & Diab, 2015). This suggests that for extension service delivery to achieve a much-desired outcome in increasing adoption of climate smart adaptation technologies and productivity growth among cocoa farmers, emphasis ought to be placed on service quality.

Notably, some empirical study has investigated the drivers of farmers' climate smart adaptation choices to include the influence of access to extension service (Denkyirah *et al.*, 2017; Ehiakpor *et al.*, 2016; McKinley *et al.*, 2015; Asante *et al.*, 2014). Unfortunately, these studies failed to capture how the key utility element of extension service delivery (i.e., quality of extension service) affects the climate smart adaptation choices of cocoa farmers. This is very important in influencing the decision behaviour of farmers in the face of the increasing consequence of climate change. Given this, the current study sought to evaluate the causal effect of extension service quality on the adoption of climate smart adaptation technologies to provide empirical support to its sequential impact on productivity and livelihood security improvement (which for this study context is indicated by food security). Furthermore, it is noted that for extension service to be relevant in contributing to the argument on how to minimise the effect of climate change on cocoa productivity, there is the need for a climate smart cocoa extension service as an improvement in the cocoa extension service delivery. However, due to the rising pressure on the government budget from the competing sectors of the economy, and the high disparity in the extension agent-to-farmer ratio; the free-to-use extension model becomes deficient. Thus, there is a need for promoting a cost-sharing extension service engagement to supplement the free-to-use one. To this end, the current study adopts a discrete choice experiment approach under a mixed logit framework to elicit cocoa farmers' preferences and estimate their willingness to pay for a climate smart cocoa extension service.

In addition, within the concept of productivity improvement, the key ingredient is how efficient available resources and technologies are employed, and not the quantum of technology transferred to farmers (Inkoom & Micah, 2017; Ettah & Nweze, 2016; Coelli *et al*., 2005). Premised on this, some empirical studies have investigated the economic, technical, and allocative efficiencies in cocoa production and their determinants (Danso-Abbeam *et al*., 2018; Obeng & Adu, 2016; Yahaya, Karli, & Gul, 2015; Onumah *et al*., 2013; Aneani *et al*., 2011). However, these studies failed to capture the role of the adoption of CSA practices on farm-level efficiency. Thus, creating a significant knowledge gap that needs to be filled on the causal effect of the adoption of CSA practices on farm-level efficiency in cocoa production to lend empirical support to the productivity impact of climate smart adaptation. Furthermore, although some studies have examined the productivity impact on food security in cocoa production (Dei Antwi, Lyford, & Nartey, 2018; Danso-Abbeam *et al*., 2018; Schouten, 2016), there is currently limited empirical evidence on the sequential causal impact of the nexus between extension service quality, climate smart adaptation and efficiency of production on food security. And this as argued above, is critical to comprehensively address the livelihood security impact of the persistent low farm-level productivity and the adverse consequence of climate change. To fill this significant knowledge gap, the current study in following a sequential causal framework under a transitivity rational, test the null of food security implication of the nexus between extension service quality, climate smart adaptation, and efficiency of production among cocoa farming households in Ghana.

1.3 Objectives of the Study

The general objective of the study was to examine the nexus between extension service quality, use of CSA practices, efficiency of production, and the implication for food security situation among cocoa farmers in Ghana.

Specifically, the study sought to:

1. Examine how climate change and variability perception influences climate smart adaptation (CSA) choices among cocoa farmers.
2. assess how perceived extension service quality influences farmers' willingness to pay for a climate smart cocoa extension service.
3. analyse the economic efficiency of production among cocoa farmers.
4. characterise the household food security situations among cocoa farmers.
5. explore the causal effect relationship between extension service quality, adoption of CSA practices, efficiency of production, and household food security status among cocoa farmers.

1.4 Research Questions and Hypotheses

1.4.1 Research Questions

To have a better understanding of the research problem and give a direct and clear focus on the study, the specific objectives were turned into questions. These are:

1. What are the significant drivers of cocoa farmers' climate smart adaptation choices in Ghana?

2. Does climate variability perception have significant implication on farmers adaptation response to climate change?
3. Does perceived extension service quality significantly explain cocoa farmers' willingness to pay for climate smart cocoa extension service?
4. Do farmers exhibit significant inefficiency (technical, allocative, and economic) effects in production?
5. Are cocoa farmers food secured?
6. Does the quality of extension service significantly explain the adoption of climate smart adaptation technologies among farmers?
7. Does the adoption of climate smart adaptation practices significantly explain the efficiency of production differentials (technical, allocative, and economic efficiencies) among farmers?
8. Does the efficiency of production (technical, allocative, and economic efficiencies) significantly explain the food security status among farmers?

1.4.2 Research Hypotheses

1. H_0: Climate variability perception does not positively and significantly influence climate smart adaptation choices among farmers

   H_1: Climate variability perception positively and significantly influence climate smart adaptation choices among farmers
2. H_0: Quality of extension service does not positively and significantly influence willingness to pay for climate smart cocoa extension service

   H_1: Quality of extension service does not positively and significantly influence willingness to pay for climate smart cocoa extension service
3. H_0: There is no significant inefficiency effect in cocoa production among cocoa farmers

H_1: there is a significant inefficiency effect in cocoa production among cocoa farmers

4. H_0: Quality of extension service does not positively and significantly influence the adoption of CSA practices among farmers.

   H_1: Quality of extension service positively and significantly influence the adoption of CSA practices among farmers.

5. H_0: Adoption of CSA practices does not positively and significantly influence the efficiency of production (economic, technical, and allocative) among farmers.

   H_1: Adoption of CSA practices positively and significantly influence the efficiency of production (economic, technical, and allocative) levels among farmers.

6. H_0: Efficiency of production (economic, technical, and allocative) does not positively and significantly influence the food security status among farmers.

   H_1: Efficiency of production (economic, technical, and allocative) positively and significantly influence the food security status among farmers.

1.5 Significance of the Study

In recent times, the issues of the adverse consequences of climate change and persistent low farm-level productivity on the livelihood security enhancement of farmers have received global attention. This study argued that an understanding of the role of quality extension service, climate smart adaptation, and efficiency of production on productivity and livelihood security improvements is critical to providing sustainability solutions to the problem. In addition, there is a growing concern for more empirical evidence on the relationship between climate variability perceptions and climate smart adaptation choices among farmers. Again, the increasing incidence of climate change and its effects calls for a climate smart cocoa extension service. However, there is limited empirical literature on these issues especially in the cocoa landscape in Ghana. Accordingly, the current study focused its research attention on investigating climate variability perceptions and climate smart adaptation choices, and the interplay that exists between extension service quality, climate smart adaptation, farm-level efficiency, and food security. In addition, the study investigated how extension service quality affects farmers willingness to pay for climate smart cocoa extension service.

It is anticipated that findings on the relationship between climate variability perception on climate smart adaptation choices will provide a solid intellectual foundation for the development of appropriate policies to manage climate change effects on cocoa farmers. Evidence on how extension service quality affects farmers' willingness to pay will give direction to stakeholders in the cocoa industries in what attributes to consider in developing and providing climate smart cocoa extension services to farmers. Information derived from the study will provide a road map on how to address bottlenecks to farm-level inefficiencies to achieve higher productivity improvement. It is believed that the evidence from this study will provide information to the government and appropriate authorities on how to improve farm household food security and resilience to climate change through the promotion of quality extension services, adoptions of climate smart adaptation practices and better farm-level efficiency.

In addition, to develop an appropriate framework for sustainable cocoa production in Ghana, empirical evidence on extension service quality, the efficiency of production, the adoption of climate smart adaptation practices, and household food security is of extreme importance. The empirical evidence will provide a useful framework to the cocoa stakeholders on how to comprehensively frame the productivity enhancement and climate smart cocoa production programmes to achieve much success to significantly increase productivity, resilience (adaptation), and food security situation among farming households. Again, the current study does have policy implications for the sustainable development goals; in that, it will provide sound and empirical evidence that can feed into the achievement of SDG 1 (ending poverty), SDG 2 (zero hunger or reducing food insecurity), SDG 12 (responsible consumption and production) and SDG 13 (climate actions) respectively.

1.6 Delimitations

Although the adverse effect of climate change is a national concern; calling for extensive research attention across the larger agricultural landscape, the current study focuses on climate change effects on cocoa production in Ghana. Secondly, the analysis centres on the food security implication of extension service quality, climate smart adaptation, and efficiency of production nexus among cocoa farmers in Ghana.

1.7 Limitations

One key challenge encountered during the survey was financial resources as the researcher was not able to secure funding from the University as initially anticipated. The multidimensional food security framework as used in this study was focused on the four food security dimensions (i.e., availability, accessibility, utilisation, and stability) as proposed by the FAO (2008). Also, the study utilised cross-sectional data for its analysis.

1.8 Definition of Terms

Agricultura Extension Service: agricultural extension service is the process that helps farmers become aware of improved technologies and adopt them in order to improve their efficiency, income, and welfare.

Economic efficiency: the ability of a farm firm to produce maximum output from minimal input combination at the least cost, assuming a cost minimising objective.

Technical efficiency: the ability of a farm firm to produce maximum output from minimal input combination

Allocative efficiency: the ability of a farm firm to produce maximum output using a cost-minimising input proportion

Climate Change: a statistically significant variation in either the mean state of the climate or in its variability, persisting for an extended period [typically decades or longer].

Climate smart adaptation: the adjustment in natural or human systems in response to current or expected climate variability and change and their effects which help to moderate harm and exploit beneficial opportunities

Climate smart cocoa extension service: the kind of extension service that provides capacity building for farmers to transition towards an enhanced and efficient climate smart cocoa production system, whiles protecting them from climate change (including climate variabilities and extremes). Such a service is believed to results in building farmers' capacity to access, acquire and efficiently utilise climate information and service in their production activities.

Food security: Situation when people at all times have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life. It has four main dimensions: Food availability, Food accessibility, Food utilisation and Food stability (vulnerability dimension)

Household Food Security Index (HFS/MHFS index): This is an arithmetic computed index that defines the extent to which a household can be considered as food secured or food insecured. The index ranges from 0 to 1, where a movement of zero to one indicates increasing the degree of household food security and the reverse implies increasing severity of household food insecurity.

Extension service quality: the ability of service providers to provide promised services to the optimal satisfaction of consumers or service users; indicated by matching service performance against customer expectations.

Willingness to pay: decision-makers (consumers and producers) willingness to pay for a change in the quality of a product with respect to specific product attributes.

1.9 Organisation of the Study

The study is organized into eight chapters. Chapter one discusses the introduction to the study. Chapter two discusses the review of related literature and the conceptual framework of the study. Chapter three discusses the research methods focusing on the methodological and analytical techniques employed in the study. Chapters four to seven presents the empirical results and discussion in line with objectives. Chapter eight presents a summary of key findings, conclusions, recommendations, and suggestions for future studies.

1.10 Chapter Summary

The chapter discussed the background to the study, the statement of the problem, objectives of the study, research questions and hypothesises, significance of the study, limitation, delimitation of the study, definitions of terms and organisation of the study. In summary, this chapter placed the rationale of the study in perspective, highlighting the needs of the study and its potential contribution to knowledge. The next chapter presents the literature review.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The chapter presents literature on the theoretical underpinnings for farmers decision behaviour with a central focus on utility maximisation and optimisation theory. In addition, sub-specific theories founded upon the utility maximisation and optimisation theory are discussed. These include expectancy disconfirmation theory, discrete choice theory, the theory of production economics and efficiency, the economics of climate smart adaptation choices, the multidimensional food security framework, and the counterfactual theory of causation. Again, the chapter covers empirical literature on the determinants of willingness to pay, determinants of agricultural extension service quality, drivers of climate smart adaptation choices, the efficiency of production and its determinants and food security of farm households. Finally, the conceptual framework of the study is discussed.

2.2 Theoretical Review

2.2.1 Central Theory Underpinning the Study: Theory of Utility Maximisation and Optimisation

Individual decision-making behaviour in relation to consumption and production has its theoretical underpinnings founded in behavioural economic theories of utility maximisation and optimisation. The current study posits that farmers are economic agents and that they make choices that maximise their economic objectives, subject to constraints. Again, as economic agents, farmers often must make decisions without complete information about all aspects of their decisions, thus, presenting uncertain consequences of outcomes. With this, the best approach to understanding their decision behaviour is to apply the behavioural economic theory of utility maximisation and optimisation. Accordingly, the theoretical and conceptual foundation of the current study is premised on utility-maximisation and optimisation theory.

The concept of utility maximisation postulates a utility function that measures the extent to which individual economic agents (consumers and producers) aggregate objectives are achieved as a result of their choice decisions or actions (Wakker, 2010; Ogaki & Tanaka, 2017; Pindyck & Rubinfeld, 2013; Rasmussen, 2011; Dixit, 1990; Lancaster, 1966). That is, individual economic agents seek to get the highest satisfaction from their economic decisions and actions. Technically, the aggregate objectives subject to endogenous and exogenous constraints present a choice problem under uncertainty; requiring that economic agents make optimal choice combinations that maximise their utility. Accordingly, utility maximisation reflects, therefore, an optimisation problem regarding the utility function and the endogenous and exogenous constraints (Flache & Dijkstra, 2015; Rasmussen, 2011; Dixit, 1990). From this premise, the individual economic agent is faced with the following problem: a set of choices subject to endogenous and exogenous constraints, and how to choose the alternative that maximises their utility. For instance, in the case of a farmer as a producer, the goal might be to maximise profit subject to the constraint of existing technology, climate change and scarcity of production resources (Mankiw, 2020; Mandy, 2016; Rasmussen, 2011; Dixit, 1990).

Furthermore, for a farmer as a consumer, the goal might be to maximise utility (livelihood security, for example, food security) subject to the constraints imposed by household income, existing market prices of commodities and available household food production (Flache & Dijkstra, 2015; Mandy, 2016; Rasmussen, 2011; Dixit, 1990). This suggests that to achieve the objective function of profit maximisation individual farmer as a producer must, therefore, make optimal choice alternatives from the set of decision alternatives as well as optimal use of scarce resources that maximise utility subject to the constraints. In addition, as consumers, farmers will have to allocate their income in such a way as to maximise their satisfaction from consuming those goods and services purchased at existing market prices. Under the concepts of utility maximisation and optimisation, given a set of choice alternatives, an economic agent chooses the alternative or actions that maximize utility subject to his/her formed expectation. In doing so, they employ the concept of optimisation to optimise their choices from the available alternatives, subject to constraints. This then implies that individual economic agents when faced with an alternative cause of action subject to constraints, must make the choice that optimises utility. Following this fundamental concept of utility maximisation and optimisation, several economic decision models have been developed to understand specific decision-making behaviour of economic agents under different conceptual frameworks; some of which have been adopted for the current study to help address the specific objectives of the study.

The underpinning sub-specific utility maximisation and optimisation theory for the analysis of extension service quality was the expectancy disconfirmation theory. The utility maximisation and optimisation theory that informed analysis of farmers preference and willingness to pay analysis was the discrete choice theory. Additionally, the sub-specific utility maximisation and optimisation theory that guided the analysis of farm-level efficiency of production was the theory of production economics and efficiency. The underpinning sub-specific utility maximisation and optimisation theory that informed climate smart adaptation analysis was the economic theory of climate smart adaptation choices. Under the rubric of utility maximisation and optimisation, the multidimensional food security framework guided the food security analysis in this study. Lastly, for the sequential causal link relationship under the transitivity rationale, the study followed the counterfactual theory of causation as the sub-specific utility maximisation and optimisation theory. The detailed discussion of these sub-specific utility maximisations and optimisation theories and how they informed this study are discussed in subsequent sections.

2.2.1.1 Expectancy Disconfirmation Theory: Theoretical underpinning for service quality measurement

Under the framework of utility maximisation and optimisation, experts in the area of consumer behaviour in service marketing have postulated the expectancy disconfirmation theory as a fundamental theory that underpins the measurement of service quality (Parasuraman, Zeithaml & Berry, 1991; Cronin & Taylor, 1994). The theory has two paradigms of expectation-performance discrepancy and performance-only discrepancy. From the disconfirmation paradigm, service quality delineates the discrepancy between consumers' expectations and their perceptions of service performance as experienced (Ali & Raza, 2017; Parasuraman *et al*., 1988; Cronin & Taylor 1994). Accordingly, service quality refers to the comparison consumers make between their expectations and their perceptions of the service received (Parasuraman, Zeithaml & Berry, 1985, 1988, 1991). In other words, service quality defines the ability of a service provider to offer efficient services to the optimal satisfaction of consumers (Abdel-Ghany & Diab, 2015; Adil, Al Ghaswyneh, & Albkour, 2013).

From the performance paradigm of the theory, service quality is directly related to the perceived performance features of the service (Cronin & Taylor 1994). The two theory paradigms put together suggest that customer satisfaction as utility indicator is a function of service quality, which is also a function of the expectation-performance discrepancy or performance-only discrepancy of service quality. It involves the assessment of service performance against consumer expectations through either expectation-performance or performance benchmarking model. This helps to address the quality gap identified in any service provision (Unidha, 2017; Gulc, 2017; Adil *et al*., 2013; Park & Yi, 2016). In line with the theory, the interpretation of service quality has followed five main dimensions as proposed by Parasuraman *et al*. (1985). These include tangibility, reliability, responsiveness, assurance, and empathy. The tangibility dimension evaluates service quality by assessing the appropriateness of both physical, human, and technological resource capacities required to provide effective and efficient service to consumers. The responsiveness dimension evaluates the willingness of service providers to provide rapid response to concerns of consumers and their ability to provide prompt service to consumers. The reliability dimension, on the other hand, evaluates the ability of service providers to appropriately provide accurate and dependable services as promised. The assurance dimension evaluates the knowledge and courtesy of service providers and their ability to convey trust and confidence. Lastly, the empathy dimension of service quality assesses the ability of service providers to identify themselves with consumers' concerns, understand their problems and accurately fix it through specialized individual attention.

Evaluation of service quality from consumers' point of view follows two main elicitation approaches. That is, consumer satisfaction survey (*ex-post*-based approach) and consumer preference survey (*ex-ante*-based approach) (Abdel-Ghany & Diab, 2015; Saini, 2018; Pinto, Costa, Figueira, & Marques, 2017). These two approaches posit that consumers' assessment of service quality is a function of the utility they derive from the use of the service. In literature, the two commonly used models used to measure service quality are the SERVQUAL model and SERVPERF model (Adil *et al*., 2013; Fleischman, Johnson, & Walker, 2017; Johari & Zainab, 2017; Saini, 2018). The former was postulated by Parasuraman *et al*. (1985) following the expectation-performance discrepancy paradigm whiles the latter was postulated by Cronin and Taylor (1994) following the performance-only discrepancy paradigm.

The SERVQUAL model follows the performance-expectation discrepancy modelling approach to measure service quality by comparing consumers' experience of the service against their expectations (Ali *et al*., 2017; Alnaser, Ghani, & Rahi, 2017; Meesala & Paul, 2018; Teshnizi, Aghamolaei, Kahnouji, Teshnize, & Ghani, 2018). It provides relevant information to service providers on the discrepancy in the service delivered in relation to consumer satisfaction. For instance, if the difference between expectation and performance is positive, consumers are said to be satisfied; but if the difference is negative, then, consumers are dissatisfied with the service (Meesala & Paul, 2018; Johari & Zainab, 2017; Saini, 2018). Due to the unique ability of the SERVQUAL model to simultaneously elicit consumer expectation and performance, the model has received extensive application in literature across different disciplines. However, one critical limitation I find with the SERVQUAL model is the potential cognitive discrepancy by respondents in simultaneously responding to both expectation and performance items at the same time. Also, when applied under a cross-sectional survey setting, the issue of time differential which is necessary for a reliable evaluation of service quality for a better description of consumer preference and customer satisfaction is not adhered to. Other key authorities in service quality modelling have also criticised the SERVQUAL model as a good fit in terms of efficient measurement of service quality (see, Cronin & Taylor, 1994; Brown, Churchill, and Peter, 1993). For instance, Brown *et al*. (1993) argued that by using the SERVQUAL model, any researcher may find different scores according to different mental construction of the respondents.

Furthermore, Cronin and Taylor (1994) argued that the elicitation of expectation and performance at the same point in time as been employed by in SERVQUAL model is clouded with construct inconsistency. They posit that not all service users can express the difference between expected service quality and perceived service quality, especially when the two assessments are done at the same time. To address the convergent and discriminant validity shortcomings of the SERVQUAL model Cronin and Taylor (1994) proposed the SERVPERF model. The model avoids the criticism associated with the dimensional structure to the interpretation and implementation of the SERVQUAL model (Gulc, 2017; Abdel-Ghany *et al*., 2012; Adil *et al*., 2013). The SERVPERF analytical approach follows the performance-only discrepancy modelling mechanism to measure service quality following the customer satisfaction survey approach (Cronin & Taylor, 1994; Hassan & Jafri, 2017; Syafrina, 2018).

Across the literature, the performance-only discrepancy modelling is considered more feasible and reliable ex-post evaluation approach to eliciting consumers' appraisal of service quality (Cronin & Taylor, 1994; Hassan & Jafri, 2017; Syafrina, 2018). The SERVPERF model is also considered as a good predictor of service quality as it is able to indicate deficiencies in any of the service quality dimensions and the need to be improved upon them (Hassan & Jafri, 2017;

Syafrina, 2018). Furthermore, by adopting a benchmarking approach, one can estimate the service quality gap efficiently from the use of the SERVPERF model (Cronin & Taylor, 1994; Hassan & Jafri, 2017; Syafrina, 2018; Gulc, 2017; Adil *et al*., 2013). Given the ability of the SERVPERF model to overcome the cognitive limitation which characterises the SERVQUAL model, this study followed the SERVPERF approach to assess the quality of cocoa extension service as experienced by cocoa farmers in Ghana.

2.2.1.2 Discrete Choice Theory: Theoretical underpinnings of Individual Preference and Willingness to Pay

Following the utility maximisation and optimisation theory, it is can be argued that farmers decision choice behaviour with respect to discrete choice situations centres around utility maximisation and optimisation subject to the given constraints (Aizaki, Nakatani, & Sato, 2015; Hensher, Rose, & Greene, 2005). For sound theoretical and empirical analysis, the discrete choice theory under the umbrella of utility maximisation and optimisation theory has therefore guided the analysis of consumer preference and willingness to pay. The discrete choice theory employs probability theory to explain or predict individuals' choices between a finite set of discrete choice alternatives. It postulates that the choice made by decision-makers relate to the attributes of the decision-maker and the attributes of the choice alternatives (Aizaki *et al*., 2015; Hensher *et al*., 2005; Louviere, Henser, & Swait, 2000; Lancaster, 1966). Situating this within the Lancaster utility theory implies that, utility is a function of the attributes of the product (goods and services) rather than the content of the product per se. The empirical application of discrete choice theory has followed either the stated choice method or the revealed choice method. The stated choice methods usually follow a methodological approach which relies on decision-makers making choices over hypothetical scenarios that are completely described by a set of attributes generated from an experimental design (Dadzie, 2016; Bourgeat, 2015; Aizaki *et al*., 2015; Carlsson, 2010; Train 2009; Hensher *et al*., 2005; Louviere *et al*., 2000).

In contrast, the revealed-preference approach uses observation on actual choices made by decision-makers to measure preferences in real-world situations (Hensher *et al*., 2005; Carlsson, 2010; Train 2009). The two approaches give rise to two sets of choice data: the stated-preference data and the revealed-preference data (Hensher *et al*., 2005; Train, 2009; Louviere *et al*., 2000; Aizaki *et al*., 2015). Some of the revealed choice methods that have received much attention include the hedonic pricing method, hedonic wage method, value of statistical life method and travel cost methods among others. On the other hand, the contingent valuation method, best-worst scaling method, and discrete choice experiment are the most widely used stated choice methods.

Within the discrete choice modelling framework, the utility function of an individual *n* facing a choice among *j* alternative in *T* choice situation is given as

$$U_{njt} = \beta_n^{'} x_{njt} + \varepsilon_{njt} \qquad (2.1)$$

where x_{njt} denotes product attributes, β_n' represents unknown parameters to estimate and ε_{njt} indicates a random term. In principle, the different distributional assumptions for β_n' and ε_{njt} generates different choice model specifications (Castellani, Vigano, & Tamre, 2014; Train, 2009, 2016; Hensher *et al*., 2005; Louviere *et al*., 2000; Aizaki *et al*., 2015). The decision-maker i chooses the alternative j if $U_{ij} > U_{ik}$ for all $k \neq j$. Once the nature of the observable output decision and distribution of ε_{ij} are specified, a probabilistic model is then applied to estimate the parameters of the behavioural process.

As noted by Trains (2009) the behavioural process function that relates the decision maker's choice (y) to observed factor (x) and the unobserved factor (ε) is given as $y = h(x, \varepsilon)$. Juxtaposing the behavioural process function to the utility function 2.1, the decision maker’s choice cannot be predicted exactly. Rather, the probability of decision outcome is estimated and this is given as $P(y|x) = Pr(\varepsilon\, s.t. h(x, \varepsilon) = y)$. As noted by Train (2009), an indicator function, $I[h(x, \varepsilon) = y]$ can be used to represent this probability function and it picks a value of 1 when the combined value of ε and x induces the decision-maker to choose outcome y, and 0 if otherwise. Consequently, the probability that the decision-maker chooses the outcome y is simply the expected value of this indicator function and this is expressed as $P(y|x) = Pr(I[h(x, \varepsilon) = y] = 1)$ with an integral function of $\int I[h(x, \varepsilon) = y]f(\varepsilon)d\varepsilon$.

Under the discrete choice model, the set of alternatives (choice set) must be mutually exclusive, exhaustive, and finite (Train, 2009, 2016). Mutually exclusiveness implies the decision-maker can choose only one alternative from the choice set. A choice set is said to be exhaustive when all possible alternatives are included. For a choice set to be finite implies that we can count the alternatives and eventually finish counting. Thus, discrete choice is the choice of exactly one alternative from a finite set of alternatives. To capture welfare estimates in discrete choice modelling, a price attribute representing product cost is added. Several model specifications have been used in empirical research, however, the most popular and widely used among them is the conditional logit model (CLM) and multinomial logit, with recent increasing attention on the mixed logit model (MLXM) (Dadzie, 2016; Vardakis, Goos, Adriaensen, & Matthysen, 2015; Train, 2009, 2016; von Haefen & Domanski, 2013; Hensher *et al*., 2005; Aizaki *et al*., 2015).

The conditional logit model and multinomial logit model assume independent random error with extreme value distribution, thus creating a condition known as independent from irrelevant alternatives (IIA) (McFadden & Train, 2000; Train 2009; Aizaki *et al*., 2015). The IIA assumption stipulates that the unobserved factors are uncorrelated over alternatives as well as having the same variance for all alternatives. That is, this basic choice model assumes that there is no heterogeneity in the individual preferences and that all utilities have the same variance (Train 2009; Vardakis *et al*., 2015). However, this assumption is much restrictive (Christiadi & Cushing, 2007; Train 2009). To overcome the IIA condition, the mixed logit is considered the most appropriate and flexible, as it can approximate any utility function. The mixed logit model introduces unobserved preference heterogeneity through the model parameters, and this allows for richer and more plausible substitution patterns and thus makes it an attractive tool for discrete choice modelling (McFadden & Train, 2000; Train 2009, 2016; Aizaki *et al*., 2015; von Haefen & Domanski, 2013). Technically, the mixed logit generalises the conditional logit by introducing unobserved taste variations for the attributes through the coefficients by assuming a mixing distribution. In estimating the willingness to pay value, the ratio of the alternative-specific attributes and the price attribute is taken (Train, 2009). In respect of this, the mixed model, unlike other model specifications, permits efficient estimation of the individual willingness to pay estimates.

Discrete Choice Experiment: Empirical elicitation approach for discrete choice theory under stated choice methods

In the empirical literature, the application of the stated choice method has mostly followed either contingent valuation or discrete choice experiment (Taneja, Pal, Joshi, & Aggarwal, 2015; De Luca & Di Pace, 2015; Al-Hanawi, Vaidya, Alsharqi, & Onwujekwe, 2018; Balcombe, Bardsley, Dadzie, & Fraser, 2019). In the contingent valuation approach (CV), respondents are directly asked the maximum willingness to pay for or minimum willingness to accept a hypothetical or real product. This approach is much employed in environmental evaluation studies due to its simplicity and easiness. However, because of the limited ability of CV to deliver a more reliable and accurate stated preference data for estimating willingness to pay for goods and services concerning product attributes (Guentang, 2018), the DCE has been advocated as the best alternative to CV (Gibson, Rigby, Polya, & Russell, 2016; Wang, Ge, & Geo, 2018; Kamara, Jofre-Bonet, & Mesnard, 2018).

The DCE uses an experimental approach to elicit decision maker's choice behaviour using hypothetical choice questions. It is a quantitative method for quantifying values placed on products through choice analysis made among a combination of attributes and attributed levels presented in a hypothetical experiment survey (Alagabi, Abdul-Majid, & Rashid, 2018; Lancsar, Fiebig, & Hole, 2017; Boeri & Longo, 2017). In the experimental process, respondents are presented with a set of choice alternatives for them to choose their most preferred option. The approach presents researchers, the opportunity of determining how decision maker's choices change when the attributes change (Train 2009; MacDonald, Anderson, & Verma, 2012). Technically, the elicitation process assumes that the option chosen by the decision-maker gives a proxy indication of his/her potential choice behaviour if faced with a real-world situation. Again, DCE assumes that the option chosen out of the choice set by respondents represents the highest utility experienced or to be derived.

Conceptually, because DCE is an attribute-driven approach, its validity depends on the appropriate specification of the attributes and their levels (Abiiro, Leppert, Mbera, Robyn, & De Allegri, 2014; Alagabi *et al*., 2018). An attribute in a DCE experiment defines the product characteristics and attribute levels are the values that define the range of dimensions or values assigned to each attribute (Louviere, Pihlens, & Carson, 2011). Characteristically, the attributes used are similar across all alternatives, but the levels of each attribute vary across alternatives depending on the experimental design (Aizaki & Nishimura, 2008; Guentang, 2018).

The design of DCE involves a series of systemic steps. The first step, the characterisation of the decision process involves the adoption of the correct representation and specification of the utility function. Furthermore, the second step, the identification and description of attributes involve systematic selection and definition of attributes which depends on a good understanding of the decision-makers perspective and experience. The selection process requires an extensive review of related literature and baseline surveys via focus group discussion and discussion with experts. It is also required that in selecting the number of attributes, the cognitive burden on decision-makers is considered. Furthermore, the researcher must avoid selecting attributes that correlate as it may affect the accurate estimation of the main effect of a single attribute on the choice variable. The third step involves defining a more meaningful and realistic attribute level. This helps to get a more accurate and precise parameter estimate. Hence, the researcher is required to consider the plausibility of the levels to decision-makers. Also, the levels must be actionable enough, inciting the decision-maker to make informed trade-offs between the set of alternatives presented. The assignment of levels can either be in the form of a categorical or continuous form and this must be well defined to aid decision-makers to get the right interpretation of the attribute level (Guentang, 2018; Train 2009, 2016).

The fourth step, the development of the experimental design involves the process by which the alternatives with their attributes and levels are generated to create the choice sets and questions (Jaynes, Xu, & Wong, 2017; Guentang 2018; Abiiro *et al*., 2014; Johnson *et al*., 2013). Mostly, the process uses the full factorial design or the fractional factorial design. In the full factorial design, a complete set of all possible alternatives and a combination of attribute levels are generated. The full factorial design generates a lot of choice sets, making it difficult for individuals to respond to them all (i.e., creates a cognitive burden to respondents). To reduce the cognitive burden, the fractional factorial design presents an unbiased and efficient approach to reduce the length of the choice set to a much manageable size. The reduction process does not compromise the properties of the full factorial design (World Health Organisation, 2012; Guentang, 2018). For an efficient generation of the choice set, it is required that it is both orthogonal and balanced (Johnson *et al*., 2013; Guentang, 2018; World Health Organisation, 2012). Orthogonality implies that the attributes are statistically independent of one another. A choice set is said to be balanced when attribute levels appear in an equal number of times, which then minimize the parameter variance (World Health Organisation, 2012; Guentang, 2018; Johnson *et al*., 2013). For efficient designs, it is required that the probability of a level repeating itself within a choice set is minimized (i.e., the property of minimum overlap) (World Health Organisation, 2012).

To eliminate the tendency of tying respondents down to only the selected attributes, it is required that the researcher adds a status quo option to the choice set. The omission of a status quo option forces respondents to choose between less important alternatives, thereby creating a potentially biased parameter estimate. Studies have strongly argued that since majority of DCE studies aims at estimating welfare indicators (willingness to pay and willingness to accept) the inclusion of a status quo option is a requirement for a much efficient estimation (World Health Organisation 2012; Johnson *et al*., 2013; Train 2009). Furthermore, it is required that researchers incorporate market realism in the experimental design as well as ensuring a balance between statistical efficiency and response efficiency (Louviere *et al*., 2011; Johnson *et al*., 2013; World Health Organisation, 2012; Guentang, 2018).

Another important step in the DCE is the construction of the survey instrument (e.g., questionnaire) to obtain the stated preference data from respondents. Having a more reliable and accurate instrument is premised on a good experimental design and a good understanding of the research objective. The process must take into consideration the cognitive ability of the respondents and must be presented in a way that minimizes response biases. To stimulate a higher response rate, it is usually best to use pictures, diagrams, and symbols. After a more efficient instrument has been developed through extensive literature review, focus group discussion and solicitation from expert opinion, the final questionnaire is designed and administered. The data collection process follows different approaches depending on the nature of respondents (Guentang, 2018).

The final step in the DCE is the analysis of the stated preference data. This involves data processing, econometric analysis, discussion of results and generation of policy implications. From the DCE data, each choice set contains information on the attribute level of each alternative and the chosen alternative by the respondent (Lancsar *et al*., 2017; Train 2009; Guentang, 2018; World Health Organisation, 2012). In the data processing process, each respondent is allocated several rows of data in the final DCE dataset (Train 2009; Guentang, 2018; Johnson *et al*., 2013). This, however, depends on measurement levels of the choices presented, which is either categorical or continuous (Guentang, 2018). The coding process is premised on the choice model selected for the analysis. Furthermore, the choice of the econometric model depends on the assumptions underpinning the error term of the utility function $U_{ij} = x_{ij}\beta + \varepsilon_{ij}$. Based on the distributional assumption made on ε_{ij}, the researcher may choose to use any of the following models: conditional logit model, multinomial logit model, standard logit model, nested logit model, probit model, mixed logit model among others.

2.2.1.3 Economics of Climate Smart Adaptation (CSA) Choices: Theoretical underpinnings

From an economic perspective, individual adaptation decision making behaviour is premised on the concept of utility maximisation and optimisation, which requires that the underlying objective function behind the adaptation actions is based on an optimising behaviour that maximises utility subject to climate change (Mendelsohn, 2012; IPCC, 2014; Margulis, 2009; Watkiss, 2015). This is because, the adaptation decision of individuals is often premised on the expected benefit taking into consideration the specific attributes of the choice alternatives (i.e., climate smart adaptation choices). Again, economic agents in the face of climate change ought to make an optimal choice decision and optimal use of production inputs to maximise utility. In recent times, adaptation to climate change has become a topical issue in agriculture due to the adverse impact of climate change. Adaptation as a concept has multiple definitions.

However, the widely adapted definition is the one given by the IPCC, in which adaptation to climate change is defined as the adjustment in natural or human systems in response to current or expected climate variability and change and their effects; which help to moderate harm and exploit beneficial opportunities (IPCC 2007; FAO, 2013). Within the context of economic thinking, adaptation can be described as any change in behaviour or system that an economic agent (household, firm or government) makes to reduce the harm or increases the gains from climate change (Mendelsohn, 2012; IPCC, 2014; Margulis, 2009; Watkiss, 2015).

The IPCC distinguishes several types of adaptation and these include: (i) anticipatory adaptation–adaptation that takes place before impacts of climate change are observed, thus referred to as proactive adaptation; (ii) autonomous adaptation–adaptation that does not constitute a conscious response to climatic stimuli but is triggered by ecological changes in natural systems and by market or welfare changes in human systems, thus referred to as spontaneous adaptation; (iii) planned adaptation–adaptation that is the result of a deliberate policy decision based on an awareness that conditions have changed or are about to change and that action is required to return to, maintain, or achieve a desired state; (iv) private adaptation–adaptation that is initiated and implemented by individuals, households or private entities and is usually in the actor's rational self-interest; (v) public adaptation–adaptation that is initiated and implemented by governments at all levels and is usually directed at collective needs; and (vi) reactive adaptation–adaptation that takes place after impacts of climate change have been observed (Levina & Tirpak, 2006; IPCC, 2014).

The concept of adaptation to climate change led to the development and promotion of climate smart adaptation (CSA) strategies for which agricultural systems can adapt to manage risk and recover from shock associated with climate change (including climate variability and extremes) (IPCC, 2014; Gebreyes, Zinyengere, Theodory, & Speranza, 2017). In the assessment of adaptation to climate change through CSA choices, farmers as economic agents operate under risk and uncertainty. Thus, efficient adaptations must represent the set of adaptation choices that maximise net benefits to the decision-maker. To understand the decision-making process concerning CSA choices, economic decision theories such as the theory of marginal cost-benefit analysis, random utility theory, choice theory, the theory of risk and uncertainty among others have guided the empirical assessment of adaptation to climate change. The cost-benefit analysis is premised on the argument of identifying and fostering efficient adjustments to climate change; adjustment whose marginal benefits outweigh its marginal cost (Mendelsohn, 2012; Tröltzsch *et al.*, 2016; Zenghelis, 2006). Here, the theory argues for the effort of identifying which actions that economic agents should take at each moment that would make them better off in response to either the current climate or future climate change.

The application of the random utility theory and choice within the framework of CSA is premised on the fact that the individual economic agent is a rational decision-maker, maximising utility relative to the choices in response to climate change (including climate variability and extremes) (Mendelsohn, 2012; Aryal *et al.*, 2018; Balew, Agwata, & Anyango, 2014). The argument is that the individual decision-maker assigns to each CSA choice alternative perceived utility and chooses the alternative that maximises utility. The rational economic agent (say farmers) in making the adaptation choice take accounts of available information, probabilities of events (climate change, including climate variability and extremes), and potential costs and benefits in determining preferences, and to act consistently in choosing the best choice of action (Taruvinga, Visser, & Zhou, 2016; Mendelsohn, 2012; Aryal *et al*., 2018; Balew *et al*., 2014). The application of choice theory also permits the analysis of homogeneity or heterogeneity in CSA choices among decision-makers and the farmer-specific variables that could explain the observed heterogeneity or homogeneity (Barnes, Islam, & Toma, 2013; Mendelsohn, 2012; Taruvinga, *et al*., 2016). Risk and uncertainty analysis have largely focused on economic agents' vulnerability to climate risk and risk perception towards climate change and adaptation (IPCC, 2014; Kunreuther *et al*., 2014; Barnes *et al*., 2013; Eze, Aliyu, Alhaji-Baba, & Alfa, 2018).

In the context of agriculture, climate smart adaptation is that kind of agriculture that sustainably increases productivity, resilience, reduces/removes greenhouse gases and enhances the achievement of national food security and development goals. To maximize the potential gains whiles minimizing trade-offs, CSA must consider the socio-cultural, economic, and environmental context where it will be applied (FAO, 2013; Gornall *et al*., 2010). Thus, CSA is not supposed to be a single specific adaptation technology of universal applicability, but rather an approach that requires a site-specific appraisal to find appropriate strategies and technologies. In principle, CSA is not is a new agricultural system per se, but rather it is a new approach of guiding the needed changes of agricultural systems given the need to jointly address food security and climate change (Grainger-Jones, 2011;

FAO, 2013). For this study, CSA is conceptualised as climate smart cocoa production systems that incorporate CSA practices. Some of the CSA practices that have been identified to yield benefit to farmers if adopted include use of improved crop variety, changing of planting time, optimal use of pesticides, optimal use of fertiliser, shade tree management, crop diversification, land rotation, crop rotation, mulching, mixed farming, non-farm diversification, and crop insurance among others (Asare, 2014; Denkyirah *et al.*, 2017; Okoffo *et al.*, 2016; COCOBOD, 2019).

2.2.1.4 Economic Theory of Production and Efficiency: Theoretical underpinnings of Technical, Allocative, and Economic Efficiencies Measurement

In production decision analysis, the theory of utility maximisation and optimisation stipulates that the production decisions behaviour of farmers aims at maximising their expected utility subjects to given constraints (Bogetoft & Otto, 2019; Behr, 2015). Guided by this, economic theory of production and efficiency following the concept of utility maximisation and optimisation have informed the economic analysis of farmers production behaviour. In the efficiency literature, a more rigorous and comprehensive analytical approach to efficiency estimation is attributed to the pioneering work of Farrell (1957). As posited by Farrell (1957), there are three categories of efficiency: technical efficiency, allocative efficiency, and economic efficiency. Technical efficiency represents the ability of a production unit to produce maximum output from minimal input combination (i.e., it defines the ability of a production unit to maximise output with minimal input mix, at the existing technology). Allocative efficiency represents the ability of a production unit to produce maximum output using a cost-minimising input proportion. That is, it measures the ability of a production unit to utilise given inputs in the optimal proportion given their prices.

According to Farrell (1957), economic efficiency is a measure of the overall farm-level efficiency and it defines the multiplicative effects of technical efficiency and allocative efficiency. Further, it represents the ability of a production unit to maximise output at the existing technology with minimal inputs mix at the least cost. That is, it defines the ability of a production unit to produce maximum output from a minimal input combination at the least cost. Drawing from the above definitions, it can be deductively said that, technical efficiency reflect technological efficiency (i.e., it shows how production units can utilise available technologies efficiently); and allocate efficiency reflect resource-use efficiency (i.e., it indicates the efficient allocation of available resources). Thus, economic efficiency indicates the combined effects of technological efficiency and resource-use efficiency. Across the literature, the analytical modelling of efficiency has either followed a deterministic frontier analysis approach (largely dominated by Data Envelopment Analysis [DEA]) or a stochastic frontier analysis (SFA) approach (Inkoom & Micah, 2017; Bogetoft & Otto, 2019; Behr, 2015).

Under the rubric of mathematical programming, the Data Envelopment Analysis (DEA) has dominated the deterministic frontier analysis of efficiency (Inkoom & Micah, 2017; Bogetoft & Otto, 2019; Behr, 2015). Data Envelopment Analysis is a mathematical programming-oriented frontier method for measuring the efficiency of production units, by constructing a non-parametric piece-wise frontier to predict the best practice production frontier as well as evaluate the relative efficiency of the different entities (Bogetoft & Otto, 2019; Henningsen, 2019). DEA estimation integrates two basic problems–(i) defining performance standard, the technology, (ii) evaluating achievements against the established standard (Bogetoft & Otto, 2019; Behr, 2015). The DEA does not require prior knowledge of either the distributional form of the inefficiency term or of the production technology that is in use by the production unit (Silva, Tabak, Cajueiro, & Dia, 2017; Nieswand & Seifert, 2018). The DEA techniques do not require functional specification of the production frontier (Bogetoft & Otto, 2019; Silva *et al*., 2017; Nieswand & Seifert, 2018). However, DEA as a non-parametric frontier approach fails to account for the stochastic process inherent in efficiency modelling, thus attributing observed inefficiency solely to managerial ability (Miao, Fang, Sun, & Luo, 2017; Silva *et al*., 2017). Again, the DEA model does not provide any general relationship between output and inputs of the production unit (Silva *et al*., 2017), rather it connects the effective production unit and envelopes all observation point via the piecewise frontier (Miao *et al*., 2017). Other deterministic frontier analysis approach includes distant function estimation, least-square estimation, corrected least square estimation, total factor productivity index among others (see, O'Donnell, 2018; Coelli *et al*., 2005).

In contrast, the SFA as a parametric frontier technique overcomes the limitations associated with the DEA method. Unlike the DEA which has its roots in mathematical programming, the SFA is much rooted in econometric theory. The SFA approach allows for apriori assumptions about the structure of the production possibility set and the data generation process (Bogetoft & Otto, 2019; Coelli *et al*., 2005). The SFA permits the assumption of a stochastic relationship between inputs and output (Miao *et al*., 2017; Bogetoft & Otto, 2019; Silva *et al*., 2017; Inkoom & Micah, 2017; Behr, 2015). That is, the SFA assumes that deviations from the frontier reflect not only inefficiencies but also the stochastic errors or noise in the data. This helps overcome the bias of generalising all observed inefficiency to managerial effects. Furthermore, under the SFA, a distributional assumption for the inefficiency term is assumed (Bogetoft & Otto, 2019; Silva *et al*., 2017; Inkoom & Micah, 2017). It also allows for a functional form specification of the frontier function and the two functional forms that have received wide application across literature are the Cobb-Douglas and translog functional forms (Nieswand *et al*., 2018; Bogetoft & Otto, 2019; Silva *et al*., 2017; Inkoom & Micah, 2017).

Given the strength of SFA in allowing for the decomposition of the error term into the statistical noise component and the inefficiency effect component, the current study used the SFA analytical techniques to examine the efficiency level of cocoa farmers.

2.2.1.5 Multidimensional Food Security Framework: Theoretical underpinning

Generally, under the theory of utility maximisation and optimisation, it can be argued that in the presence of scarcity farmers as rational being makes food security decisions aiming out maximising their utility from the consumption of available food by optimising the use of available resources. Given this, the concept of utility maximisation and optimisation has guided the development of food security framework in analysing the food security situations among households. Key among this framework is the FAO's multidimensional food security framework, which accordingly guides the analysis of food security in this study. Food security as a concept has seen significant definitional evolution over the years. The need for its appropriate conceptualisation and measurement came to the centre stage in the development during the 1996 World Food Summit due to its ties with poverty and slow growth (Guha-Khasnobis, Acharya, & Davis, 2007; FAO, 2006, 2014). In following the FAO, food security represents the state where people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for active and healthy life (FAO, 2014, 2017, 2018). Broadly, the analytical approach that has been followed in measuring food security falls under the objective-quantitative approach and subjective-qualitative approach. The long-standing debate has been which of the analytical approach is efficient: objective-quantitative versus subjective-qualitative (FAO, 2014; Guha-Khasnobis *et al*., 2007; Berry, Dernini, Burlingame, Meybeck, & Conforti, 2015). However, in recent times these two approaches are said to be complementary (Guha-Khasnobis *et al*., 2007; FAO, 2014). Conceptually, food security has six main dimensions: availability, accessibility, utilisation, stability(vulnerability), urgency and sustainability (FAO, 2008; 2018).

Technically, analysis of food security examines the probability of occurrence of a change from food security to insecurity or the reverse. The key tenet of the frameworks as illustrated in Figure 2.1 is the appreciation of the interactive effect among the four dimensions in the food (in)security analysis. Following the six dimensions of food security, the non-availability of food, lack of access, improper utilization and instability over a time period may lead to food insecurity. Thus, the use of a multidimensional index would reveal a deeper pattern of food security by highlighting the degree to which each dimension contributes to the aggregated index (FAO, 2008, 2018; Napoli *et al*., 2011). Napoli *et al*. (2011) posited that the use of a self-assessment multidimensional food security indicator provides a valuable pathway to addressing household food insecurity situations. For a comprehensive assessment of the multifaceted nature of food security, a multidimensional measurement index that incorporates different dimensions of food security is considered much appropriate (FAO, 2008, 2018; Napoli *et al*., 2011; Jones, Ngure, Pelto, & Young, 2013; Carletto, Zezza, & Banerjee, 2013; Guha-Khasnobis, Acharya, & Davis, 2007). Figure 2.1, therefore, presents the interactive effect between the four dimensions of food (in)security.

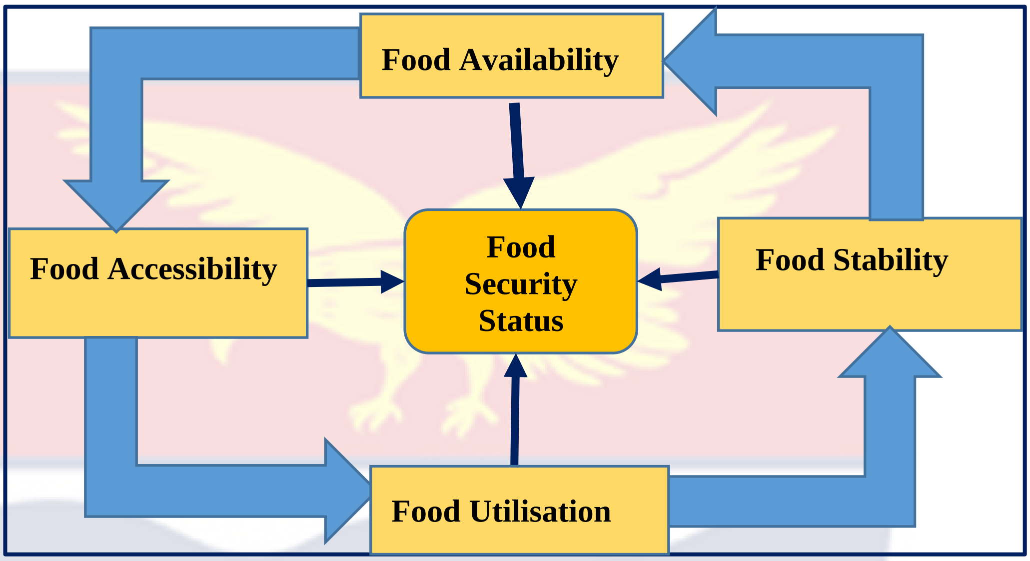


Figure 2.1: **The four dimensions of food security as defined by the FAO**

Source: FAO, (2008, 2018)

The food availability dimension focuses on the supply side of food security. It reflects the condition of people saving enough food of appropriate quality and quantity for consumption. The dimension emphasises the amount of food available to people for consumption irrespective of the source; be it domestic production, food stock, import or food aid (FAO, 2006, 2008, 2013). The food accessibility dimension looks at the physical, social, and economic access to food (FAO, 2006, 2008, 2013). It reflects the demand side of food security. It entails the ability of households and individuals of having adequate resources to obtain appropriate food for a nutritious diet (FAO, 2006, 2008, 2013). The food utilisation dimension centres on diet quality, food diversity and safety issues. It also looks at how the households or individuals decide what to consume and allocate food across the household (FAO, 2006,2008, 2013, 2014; Jones, Ngure, Pelto, & Young, 2013). The food stability dimension entails the stability of the other three dimensions over time (FAO, 2006, 2008, 2013). In addition, it looks at household vulnerability and ability to cope with food stresses and shock. It also looks at household coping strategies to food and budget deficit. Following the four dimensions, significant stripe has been made in the development of empirical indexes that efficiently capture food security. Some of these indexes include the Household Dietary Diversity Score (HDDS) index, Household Food Insecurity Access Scale (HFIAS) index, the Household Coping Strategies Index (HCS), the Food Consumption Score index (FCS) among others.

The HDDS index serves as a proxy measure of the utilisation dimension of food security. The index captures the number of different kinds of food or food groups that individuals consume over a given reference period, usually between one to seven days (Maxwell, Vaitla, & Coates, 2014; Berry *et al*., 2015; FAO 2017; Guha-Khasnobis *et al*., 2007). It follows a process of categorising the different types of food based on the nutrient they contain to determine whether the household can consume a variety of foods within the reference period. The index indicates the nutritional balance of the food consumed by the household over a reference period (Na, Gross, & West Jr, 2015; Berry *et al*., 2015; FAO, 2014, 2017). This is because a proven positive relationship between the HDDS index and improved nutritional intake has been established (Na *et al*., 2015; Hussein, Ahmed, & Muhammed, 2018). The inference from the HDDS index is that a rise in the score implies a high propensity of a household becoming food secured. The HFIAS index gives a proxy indication of the accessibility dimension of the food security framework. The HFIAS is a continuous measure for exploring the occurrences of household insecurity within a reference period, usually the past four weeks (FAO, 2008, 2014, 2017; Hussein *et al*., 2018; Coates, Swindale, & Bilinsky, 2006). The application of the scale follows two paradigms: the full version (containing 18 response items) and the reduced version (containing 6 to 9 response items). Technically, the HFIAS index looks at the propensity of households being food insecured due to lack of physical, economic, and social access to sufficient food (FAO, 2014, 2018; Hussein *et al*., 2018). The HFIAS index estimate indicates the extent of food insecurity as experienced by the household or individual. As such, the scale helps group individuals into categories ranging from food secured to severely food insecured (FAO, 2014, 2017; Hussein *et al*., 2018).

The HCS Index provides a proxy evaluation of the vulnerability or stability dimension of food security. It seeks to investigate how households manage to cope with the shortage of consuming enough food (Owino, Wesonga, & Nabugoomu, 2014; Saaka, Oladele, Larbi, & Hoeschle-Zeledon, 2017). It elicits the behaviour of households in response to food deficits or budget deficits. The HCS index is considered appropriate for measuring the impact of food aid programs as an early warning indicator of an impending food crisis and as a food security tool for emergencies when other methods are not practical or timely. One key strength of the HCS index is that it is comparatively simple and quick to use, straightforward and correlates well with more complex measures of food security (Maxwell, Vaitla, & Coates, 2014). The FCS index is a proxy measure of the availability dimension of food security. The index shows a significant correlation with the caloric consumption of households over the reference period (World Food Programme, 2012; FAO, 2017; Mathiassen, 2013). It is asserted that combining the FCS index with the HCS index provides a robust assessment of household food (in)security situation (FAO, 2017).

Generally, the above-mentioned indexes usually follow a self-assessment and experience-based approach from the perspectives of the household. And as noted by FAO (2018), the experience-based measurement produces valid and reliable quantitative measures of the prevalence of food (in)security. The above-discussed measures are often applied in a unidimensional framework which may not be the true reflection of the household food security of farm households. On this premise, this study followed a self-assessment multidimensional indices that capture all the four dimensions of food security.

2.2.1.6 Counterfactual Theory of Causation: Theoretical underpinnings for Endogenous Treatment Effect Modelling

From the counterfactual view points, individuals make an informed decision that maximises their utility based on certain preconditional factors or situations (Greene, 2012; Toomet & Henningsen, 2008). For example, farmers decision to adopt climate smart adaptation measures is preconditioned on their experience or knowledge of the occurrence of climate variability and change. The assumption is that based on the experience of climate change farmers will be motivated to adopt CSA technologies if doing so would lead to the maximisation of their expected utility. Accordingly, in analysing the sequential casual link relationship between extension service quality, climate smart adaptation, efficiency of production and food security, the counterfactual theory of causation sub-specific theory of utility maximisation and optimisation was adopted. In economic literature, the counterfactual theory of causation is typically intended to give the truth conditions of causal judgement. The underlying principle is we can capture the notion that "*x* causes *y*" by stating that, for judgement "*x* causes *y*", a certain kind of counterfactual relationship must truly exist between "*x* causes *y*" (Heckman, 1979, 2005; Greene, 2012; Toomet & Henningsen, 2008). This by implication means that to be able to arrive at a causal judgement of the kind "*x* causes *y*" requires evaluating a counterfactual such as "if *x* does not occur, y would not occur" and this demands some kind of experimental treatment (Heckman, 1979, 2005; Greene, 2012; Toomet & Henningsen, 2008). Simply put, the counterfactual theory of causation postulates that outcome variable "*y*" is only observed given that treatment or selection variable "*x*" is observed following transitivity rationale.

In the words of J.S. Mills (1843) as cited in Scott (2019), in any scientific investigation of causal inferences, three basic criteria are required to establish claims of causality: (1) a cause and effect vary in accordance with one another; (2) a cause temporally precedes an effect in a sequence of events; and (3) that alternate explanations as to how an event came about can be ruled out (i.e., no other thing could have plausibly produced the effect other than the cause). In the econometric tradition, satisfying the above three conditions, especially in observational studies requires the establishment of a counterfactual modelling approach (Morgan & Winship, 2014; Murnane & Willett, 2011; Heckman, 2005; Greene, 2012; Scott, 2019). That is, if we could establish a condition where we could observe both outcomes under the condition where the postulated cause occurred and a condition where it did not, with all other things being equal, then we would be able to lay solid claim and authentication of causality with key reference to the third criteria (Scott, 2019).

Theoretically, in building appropriate econometric tools to invoke causality claims in a cause and effect analysis, economists have treated the causal variable as a treatment or selection variable and the effect variable as the outcome variable (Heckman, 1979, 2005; Greene, 2012). Heckman, (2005) opined that causality is a property of a model of hypotheticals or counterfactuals and that the more complete the model of counterfactuals, the more precise the definition of causality between the causal variable (treatment variable) and the outcome variable. Also, our ability to rule out alternative explanations in the causal inferences between the treatment variable and the outcome variable requires randomisation (Heckman, 2005; Scott, 2019; Murnane & Willett, 2011). However, as noted by Scott (2019), observational study data are often collected from individuals acting in their own unique environments within specific contexts and thus, creating natural grouping. This introduces a problem of individual self-selection (i.e., selection bias) into treatment or grouping (Greene, 2012; Heckman, 2005) and thus resulting in a situation of non-random assignment.

Again, in most observational studies of causality, there is often a situation of mutual dependence existing among the treatment variable and outcome variable, creating a situation of endogeneity. With these issues of selection bias and endogeneity, the appropriate modelling approach of going about the counterfactual modelling is to follow simultaneous modelling of the effects of the causes as well as the modelling of the causes of the effects conditional on an event or situation. Several econometric models have been developed to handle this situation and some of these are the average treatment effect model, propensity score matching, instrumental variable estimation, and endogenous treatment effect model (Heckit treatment effect model). The Heckit treatment effect model is considered as the most flexible, as it can estimate the direct causal effect of the treatment variable on the outcome variable, hence the model choice for this study. In recent times the structural equation modelling has been also used to model counterfactual causation but does not lay strong claims to causation compared to the heckit endogenous treatment effect model.

2.3 Empirical Review

2.3.1 Empirical Review of Determinant of Agricultural Extension Service Quality

Agricultural extension service as an institutional factor in the agricultural value chain plays a key role in the diffusion of technological innovation. Thus, for efficient diffusion and utilisation of technical knowledge, farmer satisfaction with the quality of the service provided by the agricultural extension service providers is paramount. This is because the willingness and readiness of farmers to continue utilising these services is a function of the quality of the service received. In line with this, several studies have been conducted to evaluate farmers' views on the quality of agricultural extension service as well as their determinants.

A search of the literature reveals that apart from the five basic attributes of service quality (i.e., tangibility, reliability, responsiveness, assurance, and empathy), other service attributes such as timeliness of service supply, service availability, service adequacy, and access significantly influence extension service quality (Buadi, Anaman, & Kwarteng, 2013; Abdel-Ghany & Diab, 2015; Abdel-Ghany & Abdel-Salam, 2015; Rana, Reddy, & Sontakki, 2013). For instance, Buadi *et al*. (2013) noted that adequacy, availability, timeliness, and reliability of service were the most important determinants of extension service quality in Ghana. Rana *et al*. (2013) asserted that attributes such as access and timeliness were the most important determinants of extension service quality in India. Additionally, whereas Abdel-Ghany and Diab (2015) reported that reliability, responsiveness, and empathy are the most important determinants of extension service quality, Abdel-Ghany and Abdel-Salam (2015) found tangibility to be the most important determinant of extension service quality among the five basic-attribute of service quality as originally propounded by Parasuraman *et al*. (1985). Aside from these factors, a study by Elias, Nohmi, Yasunobu, and Ishida (2016) revealed that perceived economic return, regular extension contact, family size and off-farm income, limited technology choices, high input prices, credit scheme and the undefined boundary between the extension services and the local politics are important determinants of extension service quality. Furthermore, other empirical findings have shown that the farmer-specific characteristics of service users such as age, gender, education, and household income among others are significant determinants of perceived extension service quality (Min & Khoon, 2013; Christia & Ard, 2016).

2.3.2 Empirical Review of Determinants of Farmers' Willingness to Pay (WTP) for Improved Agricultural Extension Services

In agricultural production, extension service is an important vehicle of change, capable of generating desirable productivity growth via an effective and efficient transfer of technical knowledge, new technology and innovation to farmers. In the current dispensation, given the issue of climate change, an extension scheme must have as an integral part, a climate smart cocoa extension service. However, effective delivery of this service comes at a cost. Hence, understanding farmers' willingness to pay for extension service is of utmost importance for the development of appropriate climate smart cocoa extension services for cocoa farmers. For instance, a study by Ozor, Garforth, and Madukwe (2013) revealed that the most important factors that positively influence their willingness to pay for extension service include occupation, years of schooling and farm income. Furthermore, Charatsari, Papadaki-Klavdianou, and Michailidis (2011) noted that the factors that influence farmers' willingness to pay for agricultural extension services include the perceived benefit, educational level, content of the agricultural extension scheme, and mode of extension delivery.

Additionally, Ulimwengu and Sanyal (2011) reported that access to information on proposed agricultural service, distance to market, farm income, land ownership title, farm size, tend to influence farmers' willingness to pay for private extension service delivery. Again, several other studies have found out similar results where, the key determinants of farmers' willingness to pay for improved extension service include land size, education, marital status, quality of service, household income, farm size, age, media, household, and farming experience among others (Aydogdu, 2017; Temesgen & Tola, 2015; Uddin, Gao, & Mamun-Ur-Rashid, 2016).

2.3.3 Empirical Review on Determinants of Climate Smart Adaptation Choices among Farmers

The cocoa sector like any other agricultural sector is adversely affected by climate change (Denkyirah *et al*., 2017; Wiah & Twumasi-Ankrah, 2017; Okoffo *et al*., 2016). For instance, increasing climate variability (especially in terms of temperature and rainfall) is changing cropping patterns as well as the alteration in pest and disease infestation (Asante, Acheampong, Kyereh, & Kyere, 2017; Kongor *et al*., 2017). Given the socioeconomic importance of cocoa to the Ghanaian economy, an understanding of the factors that influence CSA choices of farmers will impact positively the drive to building the sector's resilience and adaptative capacity to climate change impact (including climate variability and extremes).

Literature shows that CSA choices of farmers is significantly influenced by factors such as gender, marital status, age, education, access to credit, access to extension service, risk attitudes and perception, household size, farm size, farming experience, access to information, farm income, farm output and non-farm engagement (Denkyirah *et al*., 2017; Selase, Xinhai, & Worlanyo, 2017; Khatri-Chhetri, Aggarwal, Joshi, & Vyas, 2017; Li, Juhasz-Horvath, Harrison, Pinter, &

Rounsevell, 2017; Ehiakpor, Danso-Abbeam, and Baah, 2016; Ndamani & Watanabe, 2016; Barnes, Islam, & Toma, 2013). In particular, Denkyirah *et al*. (2017) opined that access to extension service has a significant positive effect on the farmers' decision to adopt improve cocoa varieties, crop diversification, and shade tree management as CSA options. Selase *et al*. (2017) on the other hand, noted that farm management training has a significant positive effect on farmers' adoption of CSA choices.

Furthermore, farmers' perception of climate variability is said to have a significant impact on the CSA choices of farmers (Selase *et al*., 2017; Ehiakpor *et al*., 2016). For instance, Selase *et al*. (2017) noted a negative relationship between farmers' perception of climate variability and CSA choices. Ehiakpor *et al*. (2016) observed a positive relationship between farmers' perception of climate variability and CSA choices. This suggests that perception of climate variability can either encourage or discourage farmers from adopting CSA strategies. Other studies have revealed that farm tenure, location of farms, residential status, access to agricultural land, age of cocoa farm, have a significant influence on the CSA choices among farmers (Akrofi-Atitianti, Ifejika Speranza, Bockel, & Asare, 2018; Acquah, Kendie, & Agyenim, 2017).

2.3.4 Empirical Review of Determinants of Farm-Level Efficiency among Farmers

Given the basic economic problem of resource scarcity, farm-level efficiency is an important consideration for significant and sustainable productivity growth. Literature reveals that farmers in general exhibit considerable levels of technical, allocative, and economic inefficiencies (Fadzim, Aziz, & Jalil, 2017; Inkoom & Micah, 2017; Abawiera & Dadson, 2016; Aneani *et al*., 2011). Thus, comprehensive knowledge of the factors that account for farm-level efficiency differentials among farmers is necessary.

Determinants of Technical Efficiency Differentials among Farmers

Technical efficiency level among farmers is an important indicator of the productivity performance of farmers with respect to the efficient application resources at the exiting technology. In view of this several empirical studies have been carried out to assess the factors that drive the level of technical efficiency among farmers. For instance, Empirical studies reveal that farmer-specific characteristics such as age, gender, household size, education, farming experience among others do have a significant effect on the farm-level technical efficiency of farmers (Inkoom & Micah, 2017; Nicodeme & Suqun, 2017; Fadzim, Aziz, Mat, & Maamor, 2016; Ogunniyi, Ajao, & Adeleke, 2012). For instance, Ogunniyi *et al*. (2012) observed that the age of farmers had a negative relationship with the technical efficiency of farmers. For example, whereas Inkoom and Micah (2017) noted a positive effect of access to credit on the farm-level efficiency of farmers, Besseah and Kim (2014) observed that access to credit was negatively related to the farm-level efficiency of farmers. Again, Pratama, Rauf, Antara, and Basir-Cyio (2019) report that the use of quality of seeds, organic fertiliser, frequency of extension visits, training of farm managers, access to credit, access to market, sex of farmers positively influenced the technical efficiency differentials among farmers. Besseah and Kim (2014) noted that crop diversification as a climate smart adaptation option had a positive influence on the farm-level efficiency of farmers.

Determinants of Allocative Efficiency Differentials among Farmers

Assessment of the allocative efficiency level among farmers helps identify the degree to which resources are efficiently utilised and allocated with a cost minimising approach. To identify the contributing factors that account for allocative efficiency differentials, several studies have been undertaken. For instance, empirical studies reveal that farmer-specific characteristics such as age, gender, household size, education, number of crop enterprise, use of hired labour, access to credit, farm size, farming experience among others do have a significant effect on the farm-level allocative efficiency of farmers (Okello, Bonabana-Wabbi, & Mugonola, 2019; Inkoom & Micah, 2017; Nicodeme & Suqun, 2017; Haile, 2015; Arindam & Kuri, 2011). For instance, Inkoom and Micah (2017) observed that education and farming experience negatively affect the allocative efficiency levels among farmers. Okello *et al*. (2019) observed that access to credit and farm size had a significant negative effect on allocative efficiency among farmers.

Determinants of Economic Efficiency Differentials among Farmers

Evaluation of economic efficiency gives the overall farm-level productivity performance as it reveals the combined situation of technical and allocative efficiencies. As such, an understanding of the factors that accounts for observed farm-level economic efficiency differentials is key for appropriate policy intervention. Given this, some empirical studies reveal that farmer-specific characteristics such as age, gender, household size, education, farming experience among others do have a significant effect on the farm-level economic efficiency of farmers (Inkoom & Micah, 2017; Nicodeme & Suqun, 2017; Fadzim, Aziz, Mat, & Maamor, 2016; Haile, 2015; Ogunniyi, Ajao, & Adeleke, 2012). In specific, Nicodeme and Suqun (2017) and Inkoom and Micah (2017) observed that the age of farmers showed a positive effect on the economic efficiency of farmers. Furthermore, variables such as access to extension service, access to credit, membership to farmer-based organisation, farm size, and inputs cost exhibit a significant relationship with the farm-level efficiency of farmers (Nicodeme &

Suqun, 2017; Inkoom & Micah, 2017; Haile, 2015). Additionally, other studies have reported a significant effect of the adoption of climate smart adaptation strategies, sustainable agricultural practices, and migration on farm-level efficiency of farmers (Besseah & Kim, 2014; Ogundari, 2013).

2.3.5 Empirical Review of Determinants of Food Security status among Farmers

A surf of literature shows that farmers are among the category of people with high vulnerability to food insecurity at varying degrees. Hence, knowledge on factors that contribute to their exposure to food insecurity is of utmost importance. Studies have revealed that farmer-specific variables such as gender, age, marital status, education, household size, monthly household income, off-farm income, and dependency ratio significantly affect the food security situation of farmers (Osei, Aidoo, & Tuffor, 2013; Namaa, 2017; Dei Antwi *et al*., 2018). Whereas Osei *et al*. (2013) noted a negative effect of education on household food security, Namaa (2017) observed a positive effect of education on household food security. One unique finding across some of the literature was that household size had a negative influence on household food security (Osei *et al*., 2013; Dei Antwi *et al*., 2018).

Furthermore, literature shows that farm-specific variables such as farm size, total farm output, credit access, access to extension and other production resources have a significant impact on household food security among farmers (Namaa, 2017; Dei Antwi *et al*., 2018; Nyamekye, 2015). For instance, according to Namaa, (2017) access to credit exhibits a positive relationship with household food security status. Nyamekye (2015) reported a significant positive correlation between access to agricultural production resources and household food security. Added to these identified factors is the issue of climate change impact on food security. For instance, studies have found a significant relationship between climate variability, climate change and climate smart adaptation on household food security (Ali & Erenstein, 2017; Lopez-Ridaura, Frelat, van Wijk, & Valbuena, 2018; Poudel, Funakawa, & Shinjo, 2017; Haile, Wossen, Tesfaye, & von Braun, 2017). In addition, some studies have reported a significant relationship between adaptation of sustainable agricultural practices and farm household food security situations (Kruzslicika, 2014; Nkomoki, Bavorova, & Banout, 2018).

2.4 Conceptual Framework of the Study: Proposed Path Modelling of the Study Variables

Technically, a conceptual framework situates the work in its proper philosophical and operational perspective. It presents the researchers' conceptualisation of the interactive relationship between the key variables of the study. Thus, to address the problem illustrated in Figure 1.1, the reviewed literature guided the formulation of a conceptual framework to guide this work and this is illustrated in Figure 2.2.

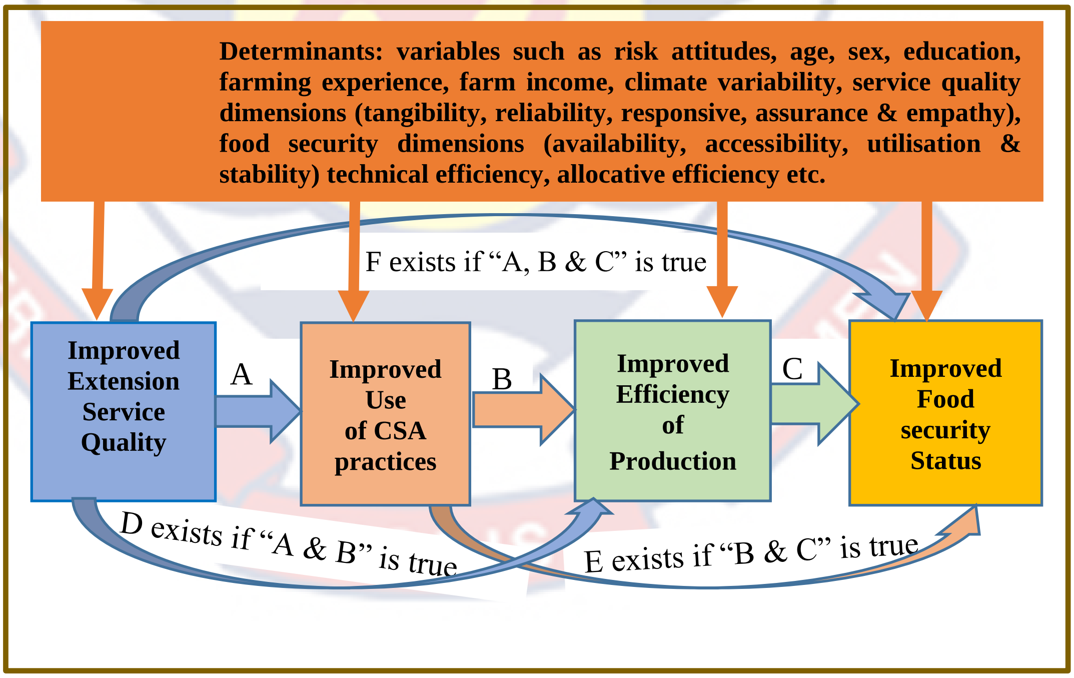


Figure 2.2: Conceptual Framework Showing the Proposed Path Modelling of the Study Variables

Source: Author's Construct, Inkoom (2019)

Figure 2.2 was formulated following a sequential causal framework under a transitivity rationale to estimate the food security implication of the connects between extension service quality, climate smart adaptation, and efficiency of production. The framework shows how extension service quality interacts with farmer choice of CSA strategy to influence farm-level efficiency and food security among cocoa farmers. As illustrated in Figure 2.2, it is hypothesised that improved extension service quality has a treatment effect implication on farmers' CSA choices. That is, an improvement in extension service quality will lead to improved adoption of CSA practices among cocoa farmers. Again, the study posits that farmers' CSA choices have a treatment effect implication on farm-level efficiency of production. Accordingly, improved adoption of CSA practices would consequently lead to improved efficiency of production among cocoa farmers. If the hypothesised relationship between improved adoption of CSA practices and farm-level efficiency of production is found to hold, then improved extension service quality indirectly affects the farm-level efficiency of cocoa farmers.

Furthermore, the study hypothesised that improved efficiency of production has a treatment effect implication on the food security situation of cocoa farmers. Here, the study posits that improved efficiency of production will lead to an improved food security status of cocoa farmers. Proven that the hypothesised relationship between efficiency of production and food security holds, then it can be assumed that improved quality of extension service, improved use of CSA practices and improved efficiency of production have a combined sequential effect on improving the food security status of cocoa farming households. From a counterfactual preposition, the import of Figure 2.2 means that if the direct relationships "A" and "B" are found to be true, then the indirect relationship "D" is also true. Again, if the direct relationships “B” and “C” are found to be true, then the indirect relationship “E” is also true. Finally, if the direct relationships “A”, “B” and “C” are proven to be true, then the indirect relationship “F” is also true. Thus, the core of the study was to explore the interactive and possible sequential causal relationship between these four constructs, following a transitivity rational.

2.5 Chapter Summary

The chapter discussed the theoretical and conceptual underpinnings of the study. It also covers literature on factors that influence extension quality, climate smart adaption choices, the efficiency of production and food security of farm households. Following the review, I believe that the study’s focus on the interaction between extension service quality, CSA, efficiency of production, and food security status brings new perspectives and dynamics to the literature on climate change economics and fills the important knowledge gaps. The next chapter presents the research methods.

CHAPTER THREE

RESEARCH METHODS

3.1 Introduction

This chapter discusses the methodological procedures that are employed in the study. It covers the research design, study area, population, sample and sampling procedure, and data collection. It also presents the data processing and the analysis procedures as applied in the study.

3.2 Research Design

The study adopted the quantitative research approach by following the positivist philosophical paradigm. The positivist paradigm allows for a deductive research approach, by starting with a theory and testing theoretical postulates using empirical data. The motivation for a positivist approach to the current study was to guarantee higher objectivity in analysing the hypothesised relationship between the variables of the study as depicted in the conceptual framework. The study employed an explanatory research design, specifically the descriptive correlational research design. The design as a quantitative method is considered appropriate for testing, exploring, and explaining hypothesised relationships that exist between observed variables and outcome variables in the population. It also permits the generalisation of research findings to the targeted study population. Furthermore, a cross-sectional survey approach was then used to obtain cross-sectional data from 720 cocoa farmers to describe and explain phenomena as they persist in the study area at the time of conducting the research.

3.3 Profile of the Study Area

The study covered all the seven cocoa-growing regions of Ghana as characterised by COCOBOD (COCOBOD, 2019). Currently, Ghana is the second largest cocoa producing country in the world and that cocoa beans from Ghana is considered as premium cocoa in the world cocoa market (COCOBOD, 2019). The seven cocoa regions as characterised by COCOBOD does not strictly follow the political-administrative regions of Ghana. The seven cocoa-growing regions as characterised by COCOBOD, therefore, include Western-North Region, Western-South Region, Ashanti Region, Eastern Region, Central Regions, Volta Region (consisting of the political-administrative regions of Volta and Oti), and Brong-Ahafo Region (consisting of the political-administrative regions of Bono, Bono East and Ahafo). The map showing the spatial dimension of the study area is thus provided in Figure 3.1.

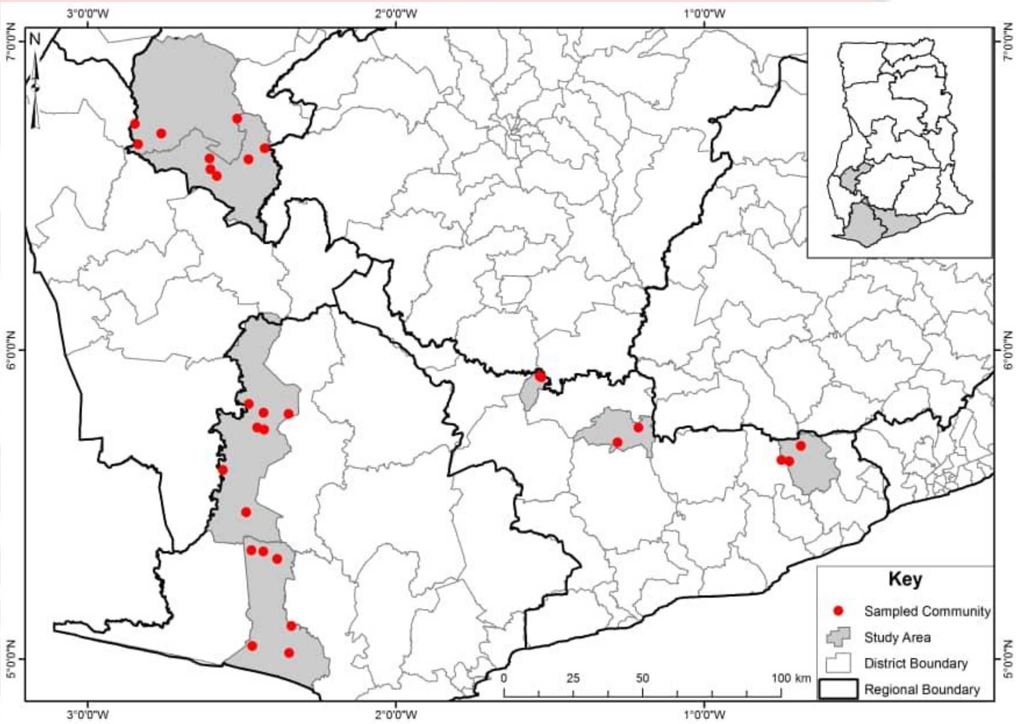


Figure 3.1: Map Showing the Spatial Dimension of the Study Area

The major economic activity across these regions is agriculture with a significant number of the farming population actively involved in cocoa production (COCOBOD, 2019). In addition, farmers across the seven-cocoa regions are significantly involved in the production of other cash, and food crops such as oil palm, rubber, coconut, yam, maize, vegetables among others. These regions share similar climatic characteristics such as rainfall pattern and distribution and temperature (COCOBOD, 2019; Ameyaw, Ettl, Leissle, & Anim-Kwapong, 2018). These regions all have a bimodal rainfall pattern with an annual average of 1000mm to 1500mm precipitation. The annual temperature across these regions often ranges from 24^{0}c to 30^{0}c (COCOBOD, 2019; Ameyaw *et al*., 2018). In general, the vegetative cover across these regions ranges from transitional to forest with some level of variation.

3.4 Population of the Study

The study population covers all cocoa farmers in the seven cocoa-growing regions in Ghana. These regions together are estimated to have a population of about 800,000 farm families who are actively engaged in cocoa production as their major economic activity (COCOBOD, 2019).

3.5 Sample Size Determination

To have an appropriate and representative sample size that is reflective of the population of cocoa farmers across the seven cocoa regions, the sample size determination formula proposed by Yamane (1967) was employed. This is given as;

$$n = \frac{N}{1+N(e^2)} \tag{3.1}$$

Where "n" represents the representative sample size; "N" is sample frame or population and "e" is the precision or margin of error. In computing the sample size, a 0.05 margin of error was assumed (i.e., 95 percent confidence interval). Furthermore, a sample frame of 800,000 farmers as currently estimated by COCOBOD for the cocoa-growing regions (COCOBOD, 2019) was assumed. Substituting these values into Equation 3.1, gave an estimated sample size of about 400 farmers. The estimated sample size of 400 farmers is considered as the minimum required sample size that is sufficient to give good representativeness of the target population. The rule of thumb is that any sample size above the estimated value increases the degree of representativeness. Accordingly, to increase the degree of representativeness the estimated sample size was increased by 80 percent resulting in a final sample size of 720 cocoa farmers from whom data was collected for the study. By increasing the sample size from 400 to 720, it helped to minimise the margin of error and increase the precision.

3.6 Sampling Technique

Seven hundred and twenty (720) cocoa farmers were sampled through a multistage sampling approach. The process was operationalized as illustrated in Figure 3.1.

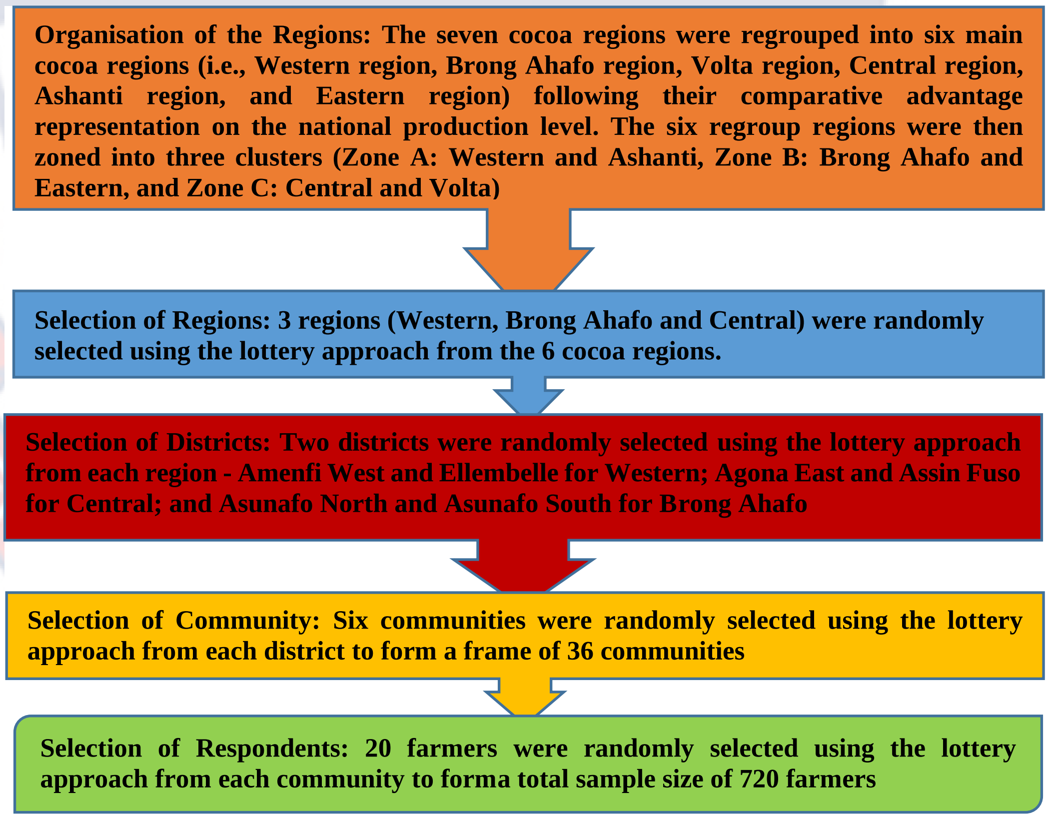


Figure 3.2: Schematic Diagram of the Sampling Procedure: A Multistage Approach

Source: Author's constructs, Inkoom (2019)

First, the seven cocoa-growing regions were regrouped into six main regions following COCOBOD national production level data reporting. Western North and Western regions were pooled together and represented as Western Region. This approach helped to align the six regrouped regions to the national production level representation data. According to statistics from COCOBOD, the ranking of the regions in terms of production level is as follows: Western Region occupies the first position; Ashanti occupies the second position; Brong Ahafo Region occupies the third position; Eastern occupies the fourth position; Central occupies the fifth position and Volta Region occupies the sixth position respectively.

Following this, the six main regions were zoned into three clusters (A, B and C) based on their comparative advantage in relation to the share of national production as given by COCOBOD. The first and second positions were placed under zone A, the third and fourth position under zone B and the fifth and six under zone C. Afterwards, the simple random lottery technique was used to randomly select one region from each zone to give a total of three cocoa regions from the pool of six cocoa regions. The selected regions include Western, Central and Brong Ahafo from where the study samples were selected. The selection of the three regions was necessitated by time and financial resource constraints. Initially, the researcher intended to cover all the six regions with the hope of securing financial sponsorship. But due to the failure in securing the funding, it became necessary to select three out of the six regions. Secondly, the list of major cocoa-growing districts in each of the three selected regions was generated and pooled together. The sample random lottery technique was then employed to randomly select two districts from each of the three regions: Amenfi West and Ellembelle from Western;

Agona East and Assin Fosu from Central; and Asunafo North and Asunafo South from Brong Ahafo. This resulted in a sample frame of six cocoa-growing districts.

Thirdly, a list of major cocoa-growing communities in each of the six selected districts was generated. The sample random lottery technique was then used to randomly select six (6) communities from each selected district to give a sample frame of 36 communities. Fourthly, a list of all cocoa farmers with at least 10 years of farming experience and a farm size of not less than 2 hectares in each of the thirty-six (36) communities were generated from each community. Afterwards, twenty (20) farmers were randomly selected from each selected community using the simple random lottery approach. The decision to select twenty farmers across board was aimed at giving equal weighting to each farmer to feed into the national sample target. By adopting this approach, the researcher was able to place equal weight on each farmers' response in describing the national picture and as well as minimise the possible skewness of the result. This finally resulted in a total sample size of seven hundred and twenty (720) cocoa farmers, from whom data was collected for the study.

3.7 Instruments for Data Collection

I employed a structured interview schedule to collect data from the selected farmers. The rationale for the choice of the instruments was to give room for the respondents to appropriately respond to questions asked. It afforded me the opportunity of obtaining accurate and adequate information on the subject matter of the study, through further probing. The instrument was divided into six parts. Part one was structured to collect data on farmers and farm-specific characteristics and production data. Part two and three was structured to collect data on climate change and variability perceptions, and climate smart adaptation choices. Part four of the instrument was structured to collect data on food security. Part five of the instrument was structured to collect data on the quality of extension service delivery. The final part of the instrument also covered a discrete choice experiment for eliciting farmers' preference and willingness to pay for climate smart cocoa extension service.

3.7.1 Description and Empirical Implementation of the DCE Design as employed in this Study

The study posits that given that farmers operate under unpredictable climatic conditions coupled with the damming effects of the increasing climate change and variability on agricultural production, the cocoa extension service needs to be climate smart through the development of an improved extension service delivery (*Climate Smart Cocoa Extension Service* [CSCES]). CSCES is defined as that kind of extension service that provides capacity building for farmers to transition towards a more climate smart cocoa production system while protecting them from climate change effects (including climate variabilities and extremes). Such a service is believed to result in building farmers' capacity to access, acquire and efficiently utilise climate information and service in their production activities. With motivation from Lancaster's theory of consumer behaviour, a DCE was designed to elicit farmers preferences and willingness to pay for the climate smart cocoa extension service scheme. The Lancaster theory stipulates that the consumption decision of individuals is a function of the utility that is derived from the attributes of the product being consumed rather than the product itself (Lancaster, 1966; Lancsar, Fiebig, & Hole, 2017; Aizaki, Nakatani, & Sato, 2015; Aizaki & Nishimura, 2008; Louviere, Henser, & Swait, 2000; Louviere, Pihlens, & Carson, 2011). The DCE process used to develop the appropriate DCE choice cards for data collection is outlined in the subsequent paragraphs.

To accurately defined and design the CSCES for the study, an extensive empirical literature search, expert's opinion, and stakeholder consultation to arrive at the product attributes were carried out. Afterwards, I further collaborated and validated the identified product (CSCES) attributes for the CSCES through expert's opinion and stakeholder consultation within the cocoa industry. The validated product attributes for the CSCES includes a monetary attribute (i.e., price) and non-monetary attributes (i.e., accessibility, content, reliability, and responsiveness). The first attribute price represents the potential service charge per month with three attribute levels of GH¢10, GH¢15, and GH¢20. This was informed by the estimated average per capita expenditure that government spend on the average farmer per production period. Available data from COCOBOD suggest that the government on average spends about GH¢106,457,600 per year on cocoa extension service delivery; suggesting an average per capita expenditure of GH¢ 200 per production period and GH¢ 20 per month. In addition to this, a further verification and authentication exercise was carried to buttress the price attributes. This was done through focus group discussion and expert opinion which suggested that farmers on average will be willing to make a monetary commitment of about GH¢ 100 to GH¢ 200 per production period for the climate smart cocoa extension service, should it be presented to them. This was then used as the basis for determining the average minimum and maximum monthly fees for the development of the CSCES scheme.

The second attribute accessibility defines the preferred mode of service delivery and access to service. It has two attribute levels: "In-person face-to-face accessibility mode which focuses on in-person face-to-face interaction" and "Virtual accessibility mode which focuses on mobile call and text message platform, mobile app and social media platforms, radio and television broadcast platforms”. The third attribute content defines the preferred service content and its perceived relevance and usefulness. This had two attribute levels: “the traditional cocoa extension service [TCES]” and “advance climate smart cocoa extension service [ACSCES]”. The advanced climate smart cocoa extension service as a content involves a comprehensive extension scheme that will have as components, climate smart adaptation packages such as shade tree management, enterprise diversification, insurance packages, irrigation package, pruning services, inputs delivery service, artificial insemination or hand-pollination service, weather information service, digital information service(Agritech) and other climate-related services that will build farmers adaptative capacity and resilience to climate change effect. The traditional cocoa extension service centres on the current existing cocoa extension that COCOBOD provides to farmers.

The fourth attribute responsiveness defines preferred frequency and promptness of service delivery and it has two attribute levels: “the fixed schedule service delivery in which contact period is made on a fixed arranged dates and time” and “the flexible demand-based service which allows for contact outside the fixed arranged periods as the need arises”. The last attribute reliability defines the extent or degree to which the service provided is accurate and dependable. This had three attribute levels "50%”, “70%”, and “90%” indicating the degree of service reliability. This was based on the understanding that farmers would not accept any service with below average service reliability as gathered from the experts and stakeholder consultation.

Having arrived at the product attributes and attribute levels, I went on to design the DCE choice card which was used to collect the stated preference data from the sampled farmers. Here, I designed choice cards that present to farmers two product alternatives as well as an opt-out. The design of the choice cards proceeds as follows: Firstly, based on the number of attributes (5) and attributes levels (2 to 3), I employed the fractional factorial design to generate representative choice sets from the full factorial design. The process involves the coding of the attributes and attribute levels after which the Support.CEs and AlgDesign packages in R programming Environment were used to generate the choice sets or cards. The product attributes and attribute levels that were coded and used to generate the product alternatives on the choice card are shown in Table 3.1.

Table 3.1: Choice Experiment Attributes and Attribute-levels used in CSCES Choice Experiment Design

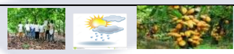
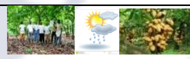
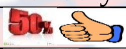
Attributes	**Attribute-levels**	**Code**
Service accessibility	Virtual accessibility mode	1
	In-person face-to-face accessibility mode	2
Service content	Traditional cocoa extension service	1
	Advance climate smart cocoa extension service	2
Service responsiveness	Fixed schedule service delivery	1
	Flexible demand-based service delivery	2
Service reliability	50 % degree of reliability	Treated as a continuous variable
	70% degree of reliability	
	90% degree of reliability	
Price per month (GHS)	10	Treated as a continuous variable
	15	
	20	

Source: Inkoom (2019)

From the full factorial design, choice sets of one hundred and eight (108) were initially generated. Now presenting these number of choice cards to farmers to respond to would be tedious and bring a cognitive burden to farmers. Also, this would usually provoke non-corporation and non-respondence from the farmers (Aizaki & Nishimura, 2008; Aizaki *et al*., 2015). To avoid this situation, it became necessary to adopt measures that can efficiently and unbiasedly reduce the number of choice sets. To this effect, the fractional factorial design approach was then applied to reduce the choice set to sixteen in two blocks of eight sets each. To have two product alternative, two copies of the fractional factorial design was created.

Afterwards, a random selection approach in the AlgDesign package was used to select four individual choice sets or cards from each block, totalling eight choice questions which were subsequently presented to farmers in the survey. This was done in appreciation of the kind of respondents being dealt with and to increase corporation and high response rate. A sample of the CSCES choice scenarios or tasks used in the choice experiment is presented in Table 3.2. During the survey, farmers were presented with a series of choice scenarios with different product alternatives consisting of different combinations of product attributes and attribute levels. As illustrated in Table 3.2, each choice situation had three alternatives (i.e., A, B and C). The experiment process was such that, farmers were to consider only the attributes explained in the choice task and treat each choice task independently.

Table 3.2: Example of the Choice Card Presented to Farmers to Respond

Attributes	**Alternative A**	**Alternative B**	**Alternative C**
Accessibility	 Virtual accessibility mode	 Virtual accessibility mode	opt-out
Content	 ACSCES	 ACSCES	
Responsiveness	Flexible Demand-Based Service Delivery	Flexible Demand-Based Service Delivery	
Reliability			
Price	 GH¢20	 GH¢15	
I would prefer	[ ]	[ ]	[ ]

Source: Inkoom (2019)

In each experiment, farmers were asked to evaluate the three options, stating which one they considered best and thus prefer. Here, farmers were to select one product alternative under each choice situation, where a selection of the opt-out suggested a preference for the status quo. The experiment was repeated until each farmer had responded to the eight different choice tasks or questions. The experimental elicitation process led to the generation of stated preference data.

3.8 Pre-testing of Instruments

A pilot study was carried out at the Effutu community in the Cape Coast metropolis of the Central region of Ghana to pre-test the validity and reliability of the instrument. The data obtained from the pilot study were coded and analysed. A reliability test was conducted for the item response section of the instrument. The Cronbach alpha test results as presented in Appendix 2, shows that all the items were reliable with an alpha value of 0.70 and above. The reliability test and preliminary analysis validate the appropriateness of the instrument. To further improve the validity and reliability of the instrument, it was subjected to peer review and the necessary suggestions was then incorporate for the actual data collection.

3.9 Data Types and Data Collection Procedures

Primary data was collected from individual cocoa farmers for the analysis. Six (6) field assistants were recruited and trained to assist in the data collection. The structured interview schedule was then administered to individual cocoa farmers in the selected communities with assistance from the trained field assistants. Farmers were interviewed on a one-to-one basis to respond to the questions in the instruments. Data collection lasted for a period of two months, from July to August 2019.

3.10 Ethical Clearance and Issues

Before the research was conducted, I sought ethical clearance from the Institutional Review Board of the University of Cape Coast. Consent was sought from the farmers after a brief introduction to the purpose of the research.

Respondents were assured confidentiality of any information provided during the interview. To protect information collected from the farmers, hard copies of the data were kept under lock accessible only to me. The soft copy of the data was then encrypted to prevent unauthorised access.

3.11 Data Processing and Analysis

After content analysis of the raw data through face validity and cross-checking, the data collected was cleaned and processed for statistical analysis using appropriate coding format. The processed data were then analysed using both descriptive statistics and econometrics models. The detailed description of the detailed analytical procedure following the objectives of the study is presented in Sections 3.12 to 3.16 respectively. The Microsoft Excel and R Programming Environment were utilised as data analysis tools. Results were presented in the form of tables and figures to give a visual appraisal of the outcomes from the study.

3.12 The Analytical Techniques and Modelling approach for Objective One

Objective one of the study sought to examine climate change and variability perception and climate smart adaptation choices among cocoa farmers. Descriptive statistics such as means and percentages were used to characterised farmers' climate change and variability perception and CSA choices. In addition, a multivariate Probit model was used to examine the significant drivers of cocoa farmers' CSA choices in response to climate change. The modelling approach is detailed in Subsections 3.12.1 to 3.12.3 respectively.

3.12.1 Estimating the Level of use of CSA Practices among Cocoa Farmers

In measuring the level of use of CSA strategies, farmers were presented with eleven recommended CSA practices (COCOBOD and Forest Trends, 2017; Asante, Acheampong, Kyereh, & Kyere, 2017; Selase *et al*., 2017; Asare, 2014; Denkyirah *et al*., 2017; McKinley *et al*., 2015) to elicit the number of adaptation strategies currently being used at the farm-level. The CSA practices include use of improved crop varieties, optimum use of fertiliser, optimum use of pesticides, practice of shade tree management, practice of changing of planting date, practice of crop diversification, practice of non-crop diversification, practice of off-farm diversification, subscription to cop insurance, practice of irrigation system, and practice of hand pollination. The binary response outcome (defining the decision to adopt) was used to generate a count-index outcome (defining the level of use—that is, the number of CSA options being used by the i^{th} farmer). Data were analysed using descriptive statistics such as frequency and percentages. To determine the overall percentage rate of awareness, the total sum of the frequencies of CSA awareness was divided by the product of the number of respondents and the number of CSA practices presented to farmers. Also, to determine the percentage rate of CSA adoption, the total sum of the frequency of use of CSA practices was divided by the product of the number of respondents and the number of CSA being practised by cocoa farmers.

In addition, awareness of climate variability (measured on a continuous score of "1= definitely very low" to "10= definitely very high), perceived impact of climate change effect (measured on a continuous score of "1= definitely very low" to "10= definitely very high), perceived future threat of climate change effect (measured on a continuous score of "1= definitely very low" to "10= definitely very high), risk perception towards investing in CSA (dummy; 1=risky to invest in, 0=safe to invest in) and effectiveness of CSA options (measured on a continuous score of "1= definitely very low" to "10= definitely very high) were statistically generated using an indexing mechanism on a scale of 0 to 1 continuum. This indexing approach follows the Human Development Index axioms promulgated by the United Nations Development Programme (The United Nations Development Programme [UNDP], 2019). Here it is assumed that to transform a raw variable (say x), into a unit-free index between 0 and 1(which allows for different indices to be added together), the ratio computation should focus on the difference between the actual value of x and the expected minimum value of x divided by the difference between the expected maximum value of x and the expected minimum value of x.

This computation approach unlike the traditional approach (i.e., $actual$ value of x $\div$ expected maximum value of x) addresses the variability discrepancy between the sample and the population estimate. This is because it is expected that all other things being equal, the average individual may either score the minimum or the maximum. In line with this, the derivation of the index scale was computed as shown in Equation 3.2.

$$Index\ scale = \frac{actual\ score - expected\ minimum\ score}{expected\ maximum\ score - expected\ minimum\ score} \tag{3.2}$$

Under the perception of climate variability, perceived impact of climate change effect, perceived future threat of climate change effect and effectiveness of CSA assessment, the actual score in equation 3.2 was represented by the mean score obtained from the rating given by the farmers to item construct. Likewise, the expected minimum and maximum scores were represented by the minimum (a score of 1) and maximum (a score of 10) responses that could be assigned to each item as presented to the farmers.

Under the risk perception measurement, the mean score in Equation 3.2 was represented by the total count of risky responses given by farmers. The expected minimum and maximum scores were represented by the potential minimum (a score of 1) and maximum (a score of 11). That is, the risky responses that could be given by farmers to the eleven recommended CSA practices presented to them. The application of Equation 3.2 led to the generation of a continuous scale ranging from 0 to 1 and that permitted the introduction of intensity assessment of the various constructs. With this, a movement from 0 to 1 depicting increasing intensity in the degree of the construct and the reverse implies a decreasing intensity in the degree of the constructs.

3.12.2 Theoretical Specification of Multivariate Probit Model

Theoretically, the multivariate Probit model is an attractive model of choice behaviour which permits a flexible correlation structure for the unobservable variables. However, the empirical application of this model has been limited due to the dimensionality problem in estimating the multivariate probabilities involved. To circumvent this problem several approaches have been proposed. Some of these include deterministic integration, Monte Carlo integration, simulation-based methods, quadrature methods and numerical integration based on maximum likelihood approach among others (McFadden, 1989; Pakes & Pollard, 1989; Lesaffre & Kaufmann, 1992; Huguenin, Pelgrin, & Holly, 2009). The multivariate probit model as a generalization of the ordinary probit model permits the estimation of several correlated binary outcomes jointly. For instance, the binary outcome of climate change awareness and adoption of climate smart adaptation practices being correlated can be appropriately estimated via the multivariate probit. In the multivariate probit model, y_{ij} denote a binary 0/1 response on the i^{th} observation unit and j^{th} variables, and $y_i = y_{i1}, \ldots, y_{ij}; i = 1, \ldots, N$ denote the collection of responses on all J dependent variables with latent variables $(y_{ij}^* = y_1^*, \ldots, y_j^*; i = 1, \ldots, N)$.

The theorem assumes that each observed variable `takes a value of 1 if and only if its underlying continuous latent variable picks on a positive value. Given this, if we take "j" as choice and "i" as observation, then the probability of observing choice "y_i" is expressed as

$$Pr(y_i|X_i\beta,\varepsilon) = \int_{A_{ij}} \cdots \int_{A_{i1}} f_N(y_i^*|X_i\beta,\varepsilon)dy_1^* \ldots dy_j^* \qquad (3.3)$$

$$Pr(y_i|X_i\beta,\varepsilon) = \int 1_{y^* \in A_j} f_N(y_i^*|X_i\beta,\varepsilon)dy_i^* \qquad (3.4)$$

where, $\mathrm{A}_{ij} = A_1 \times \ldots \times A_j$ and, $\mathrm{A}_{ij} = \begin{cases} (-\infty,0) & y_{ij}^*=0 \\ (0,\infty) & y_{ij}^*=1 \end{cases}$

Now the log-likelihood function is thus specified as

$$\sum_{i=1}^{N} logPr(y_i|X_i\beta,\varepsilon) \qquad (3.5)$$

Following Lin, Jensen, and Yen (2005) the multivariate probit model for say J binary dependent variables can be specified as:

$$logPr(y_{ij(j=1,\ldots,m)}) = x_i\beta_j + \varepsilon_{ij}; \begin{bmatrix} y_i = 1 \; if \; \beta_j x' + \varepsilon_{ij} > 0 \text{ and,} \\ y_i = 0 \; if \; \beta_j x' + \varepsilon_{ij} \leq 0 \; \{ i = 1, \ldots, n\} \end{bmatrix} \qquad (3.6)$$

Where x denotes a vector of the explanatory variables; βs are conformable parameter vectors to be estimated and ε_i represents random error distributed as a multivariate normal distribution with zero mean, unitary variance and an $n \times n$ correlation matrix.

3.12.3 Empirical Specification of Multivariate Probit Model for Assessing Factors that Influence CSA Choice Decision among Farmers

The study assumed that, with the increasing exposure and vulnerability to climate change effect, cocoa farmers may choose a mix of CSA options rather than depending on a single strategy; allowing them to exploit the complementary benefit among the options. It was also assumed that the choice of CSA strategy by cocoa farmers may be partly dependent on earlier adopted strategies; informing decisions on subsequent strategies for the future. Thus, the use of the multivariate probit model allowed for the simultaneous estimation of the influence of exogenous variables on the CSA choices of farmers. Following the simulation-based maximum likelihood estimation approach, the empirical specification of the model as applied in this study is specified as:

$$log\,Pr(\,CSA_{ij(j=1...8)}|y_j = 1) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{14} x_{14} + \varepsilon_{ij} \quad (3.7)$$

Where: $CSA_{ij(j=1-8)}$= the eight CSA choices of the i^{th} farmer; Pr = probability of a farmer choosing a particular adaptation option; βs = unknown parameters to be estimated; ε_{ij}= stochastic error term. The description of the variables as modelled in Equation 3.7 is presented in Table 3.3.

Table 3.3: Description of Variables in Equation 3.7

Variable	Description	Apriori
CSA_1	improved crop varieties (adopter = 1; otherwise=0)	
CSA_2	Optimum use of fertiliser (adopter = 1; otherwise=0)	
CSA_3	Optimum use of pesticides (adopter = 1; otherwise=0)	
CSA_4	Changing plant date (adopter = 1; otherwise=0)	
CSA_5	Shade tree management (adopted = 1; otherwise=0)	
CSA_6	Crop diversification (adopter = 1; otherwise=0)	
CSA_7	Non-crop diversification (adopter = 1; otherwise=0)	
CSA_8	Off-farm diversification (adopter = 1; otherwise=0)	
x_1	Perceived rainfall variability (*index score from 0 to 1 continuum*	+
x_2	Perceived temperature variability (*index score from 0 to 1 continuum*	+
x_3	Perceived adverse effect of climate change (*index score from 0 to 1 continuum*	+
x_4	Perceived future threat of climate change (*index score from 0 to 1 continuum*	+
x_5	Awareness of CSA options as adaptation responses to climate change (*index score from 0 to 1 continuum)*	+
x_6	Perceived risk associated with investing in CSA (*index score from 0 to 1 continuum)*	-
x_7	Sex of the farmer *(dummy; 1=male and 0 = females)*	+/-
x_8	Age of the farmer in years	+
x_9	Education (years spent in school)	+
x_{10}	farmer-based organisation membership *(dummy; 1 =member, 0= Otherwise)*	+
x_{11}	Years of farming experience	+
x_{12}	Frequency of extension contact	+/-
x_{13}	access to credit (dummy; 1=Yes, 0=Otherwise)	+
x_{14}	Farm income (measured in Gh¢)	+

Source: Inkoom (2019)

3.13 The Analytical Techniques and Modelling approach for Objective Two

Objective two of the study sought to assess how perceived extension service quality influences farmers’ willingness to pay for a climate smart cocoa extension service. Following the customer satisfaction approach, the SERVPERF model (Cronin & Taylor, 1994) was used to estimate extension service quality. Afterwards, a discrete choice experiment framework with an implementation based on the mixed logit model was employed to analyse farmers' preference and willingness to pay for a hypothetical climate smart cocoa extension service, and how that is influenced by farmers’ perceived extension service quality. The modelling approach is detailed in Subsections 3.13.1 to 3.13.6 respectively.

3.13.1 Theoretical Specification of SERVPERF Model

Theoretically, the SERVPERF model is a performance-based customer satisfaction survey approach to evaluating service quality. The SERVPERF model is an abridged version of the SERVQUAL model whereby the expectation component of the SERVQUAL is dropped. The justification is that performance-approach gives greater predictive power to service quality measurement, in that service quality is assumed to be directly influenced only by perceptions of service performance (Boulding, Kalra, Staelin, & Zeithaml, 1993; Cronin & Taylor, 1994; Abdel-Ghany *et al*., 2012). The SERVPERF model contains response items that elicit respondents’ assessment of service quality with respect to the five service quality dimensions: tangibility, responsiveness, reliability, assurance, and empathy. The elicitation procedure follows a survey approach where respondents are presented with the SERVPERF tool for them to rate their service experience (self-assessed performance evaluation) on a scale. The summated mean for each dimension defines the extent to which respondents view the service they receive to be quality. Mathematically, the model is expressed as follows:

$$SQ_i = \sum_{j=1}^{m} P_{ij} \tag{3.8}$$

Where: SQ = perceived service quality by the individual i^{th} farmer; m = the total number of items presented to the farmers; and P = the performance score assigned by the individual i^{th} farmer with respect to j service quality attribute or dimensions. The individual-specific service quality dimensions include tangibility, reliability, responsibility, assurance, and empathy.

3.13.2 Empirical Specification of SERVPERF Model for Measuring Extension Service Quality

The study assumed that cocoa farmers like any other service user are much concerned with optimal delivery of service provision. This is because the utility derived from the use of the service is the function of the quality of the service. Hence, their evaluation of service quality is a function of their affective and cognitive judgement of actual service performance as experienced. Thus, in the application of the SERVPERF model, farmers were asked to rate their perception on the performance of the quality of cocoa extension service received on a continuous scale of 1 (definitely very low) to 10 (definitely very high). The empirical model for evaluating the performance of cocoa extension service as perceived by cocoa farmers in relation to the five quality dimensions of the SERVPERF model was specified as follows:

$$SQ_i = \sum_{j=1}^{m}(PTA_{ij} + PRS_{ij} + PRB_{ij} + PAS_{ij} + PET_{ij}) \tag{3.9}$$

Where: SQ_i = overall service quality; PTA_{ij}= tangibility dimension (the appropriateness of both physical, human and technological resource capacities of extension service providers to provide effective and efficient service to consumers); PRS_{ij}= responsiveness dimension (evaluates the willingness of extension service providers to provide rapid response to concerns of consumers and their ability to provide prompt service to consumers); PRB_{ij}= reliability dimension (evaluates the ability of extension service providers to appropriately provide accurate and dependable services as promised to consumers); PAS_{ij}= assurance dimension (evaluates the knowledge and courtesy of extension service providers and their ability to convey trust and confidence); and PET_{ij}= empathy dimension (assesses the ability of service providers to identify themselves with consumers' concerns, understand their problems and accurately fix it through specialized individual attention).

Derivation of Degree or Extent of Service Quality

Following the UDNP axioms for computing index as discussed under Section 3.13.1 for Equation 3.2, an indexing mechanism as expressed in Equation 3.10 was used to compute a service quality index SQ_i (depicting the extent or degree of service quality). The index scale is bounded between 0 (definitely very low) to 1(definitely very high). A movement from zero to one implies an increasing degree of service quality and vice versa. This indexing approaches help to place the argument within the context of optimal performance frontier (SQ_i^*=1); where a score of 1 implies performance meets expectation. A score below 1 brings in the issues of the quality gap, representing a deviation from the optimal performance frontier (SQ_i^*=1). To be able to identify the service quality gap, a benchmarking approach to the SERVPERF model as specified in Equation 3.11 was employed. The application of Equation 3.11 helped identify quality shortfalls for possible intervention by the extension service providers.

$$SQ_i = \frac{\text{actual quality score - expected minimum quality score}}{\text{expected maximum quality score - expected minimum quality score}} \tag{3.10}$$

$$\mathrm{GAP}_i = f(SQ_i^* - SQ_i);\ where\ SQ_i^* = 1;\ GAP_i = 1 - SQ \tag{3.11}$$

3.13.3 Theoretical Specification of the Mixed Logit Model

Mixed logit is a highly flexible econometric model that can approximate any random utility model with an appropriate choice of variables and mixing distribution (McFadden &Train, 2000; Hole & Kolstad, 2012). The model overcomes the independence from irrelevant alternatives (IIA) condition (Train, 2009, 2016; Hess & Train, 2017). In addition, it allows for random taste variation, unrestricted substitution patterns and correlation in unobserved factors over time (Train, 2009, 2016; Hess & Train, 2017). Furthermore, the model accounts for both observed and unobserved preference heterogeneity by assuming random parameters for the model coefficient (Train, 2016; Hess & Train, 2017; Dadzie 2016; Owusu Coffie, Burton, Gibson, & Hailu, 2017). Again, the mixed logit model assumes a general distribution for the random component which can take several distributional forms such as normal, lognormal, uniform, or triangular (Train, 2009).

Under the mixed logit the utility that person n obtains from alternative j in any choice situation is expressed as:

$$U_{nj} = \beta_n^{'} x_{nj} + \alpha_n^{'} z_n + \varepsilon_{nj} \qquad (3.12)$$

Where x_{nj} is a vector of observed attributes, β_n is a corresponding vector of utility coefficients that vary randomly across individuals with a density of $f(\beta|\theta)$; where θ denote the parameters of the distribution. z_n is a set of M characteristics of individual n that influences the mean of the preference parameters (i.e., it explains the source of heterogeneity), and α_n' represents a $k \times m$ matrix of additional parameters; ε_{nj} is a random term that represents the unobserved component of utility which is assumed to be independent and identically distributed (iid) extreme value. With this assumption, the logit probability that person n chooses alternative j in any choice situation conditional on β_n, is

$$_{nj}(\beta_n) = \frac{e^{\beta_n x_{nj}}}{\sum_j e^{\beta_n' x_{nj}}},\ \text{js} = 1, \dots, J \tag{3.13}$$

Now if we consider a sequence of alternatives, one for each time $j = \{j_1, \dots, j_T\}$ conditional on β, the probability that the decision-maker makes this sequence of choices is expressed as the product of the standard logit formulas:

$$L_{nj}(\beta_n) = \prod_s \left[\frac{e^{\beta_n' x_{nj}}}{\sum_j e^{\beta_n' x_{nj}}}\right] \tag{3.14}$$

However, since β_n is random and not known, the unconditional choice probability under the mixed logit framework is the integral of L_{nj} over all possible variables of β_n (i.e., $p_{nj} = L_{nj}(\beta_n) f(\beta) d\beta$) which is expanded as:

$$P_{nj} = \int \frac{e^{\beta_n x_{nj}}}{\sum_j e^{\beta_n' x_{njs}}} f(\beta) d\beta \tag{3.15}$$

In literature, the application of the mixed logit has followed two estimation paradigms: the simulated maximum likelihood approach and the Bayesian approach. However, studies have suggested that there is a high similarity for the parameter estimates between the two approaches (Huber & Train, 2001; Elshiewy, Zenetti, & Boztug, 2017). As such the choice between the two estimations is one of implementation convenience and philosophical orientation, rather than pragmatic usefulness (Elshiewy *et al*., 2017). Premised on this, the current study followed the simulated maximum likelihood estimation approach (MSLE).

For the MSLE to produce reliable and unbiased estimates it must exhibit certain properties: consistency, efficiency, and asymptotic property. In addressing the asymptotic property of MSLE the question lies in how the simulation bias behaves as the sample size rises. Thus, to have an unbiased estimate, the number of draws (R) must rise with the sample size. Stated explicitly, the simulation bias disappears as the sample size and R rises without bound. Now if R rises at a rate faster than the sample size, the MSLE becomes much consistent and efficient. Finally, the estimation procedure will follow the Monte Carlo simulation, which allows for the estimation of the multidimensional integrals that define the choice probabilities.

3.13.4 Empirical Specification of Mixed Logit Model with Heterogeneity as Applied in this Study to Analyse Individual Preference

Following the simulated maximum likelihood estimation approach, the empirical mixed logit model with heterogeneity as applied in this study was specified as:

$$u_{nj} = \beta_o + \beta_1 x_1 +, \ldots, +\beta_5 x_5 + \beta_6 z_1 +, \ldots, +\beta_9 z_4 + \varepsilon_{nj} \quad (3.16)$$

The utility function stated above describes the optimizing behaviour of cocoa farmers regarding the choice among different CSCES product alternatives. Here it assumes that the utility a farmer obtains from choosing alternative j is a linear combination of the CSCES product attributes $(x_1 - x_5)$, farmer-specific attributes $(z_1 - z_4)$ and a random term ε_{nj}. The inclusion of the Z variables (farmer-specific attributes) helped to account for the source of preference heterogeneity in the model as specified in Equation 3.16. The βs attached to $(x_1 - x_5)$ represent vector coefficients describing the effects of product attributes on the utility of the n^{th} cocoa farmer. Additionally, the βs attached to $(z_1 - z_4)$ represent vector coefficients describing the effects of farmer-specific attributes on the mean of the coefficient estimates of the product attributes. The description of the variable that went into Equation 3.16 is presented in Table 3.4.

3.13.5 Theoretical specification of Willingness to Pay (WTP) using WTP Space approach

Traditionally, the WTP model is given as the ratio of the coefficient of non-monetary attributes to the price coefficients $(w_n = -b_n/\lambda_n)$. In the case of the mixed logit model, the ratio of two randomly distributed parameters causes a skewed distribution of WTP. To address this, Train and Weeks, (2005) suggested estimating the mixed logit model in the WTP space model. Here, WTP is directly estimated by reformulating the model in such a way that WTP of attributes coefficient are directly derived from the mixed logit model (Train & Weeks, 2005; Tu, Abildtrup, & Garcia, 2016; Scarpa, Thiene, & Train, 2008; Hole & Kolstad, 2012). The WTP space model reparameterizes mixed logit model such that the parameters are the marginal WTP for each attribute rather than the utility coefficient of each attribute (Sarrias & Daziano, 2017; Tu *et al.*, 2016; Scarpa *et al.*, 2008; Train & Weeks, 2005; Sarrias, 2016). Following the WTP space approach, the mixed logit model is re-specified to separate the price attribute from the vector of non-monetary attributes. That is, $\beta_{nj}x_{nj} = \lambda_n p_{nj} + b_n x'_{nj}$, where p_{nj} denotes the price attributes and x'_{nj} denotes a vector of other non-monetary attributes. The λ_n is a random parameter for price and b_n are the individual random parameters of other non-monetary attributes.

Following Train and Weeks, diving utility by the scale parameter K_n the utility for decision-maker n choosing alternative j in choice situation t becomes:

$$U_{nj} = -\lambda_n/k_n(p_{nj}) + (b_n/k_n)' x_{nj} + \alpha_n' z_n + \varepsilon_{nj} \tag{3.17}$$

ε_{njt} is a random term that is Gumbel-distributed and whose variance is $Var(\varepsilon_{nj}) = k_n^2(\pi^2/6)$, where K_n is the scale parameter for the n^{th} individual. If the coefficients of price and non-monetary attributes are redefined as $\gamma_n = \lambda_n/\kappa_n$ and $\eta_n = b_n/\kappa_n$, such that utility is written as

$$U_{nj} = -\gamma_n p_{nj} + \eta_n' x_{nj} + \alpha_n' z_n + \varepsilon_{nj} \tag{3.18}$$

Then, the wtp model can be rewritten as $w_n = \eta_n/\gamma_n$. Incorporating this into equation 3.17 results in a new utility function given as

$${}_{nj} = -\gamma_n p_{nj} + (w_n \gamma_n)' x_{nj} + \alpha_n' z_n + \quad {}_{nj}$$
(3.19)

Under this parameterisation, the variation in WTP, which is independent of scale, is distinguished from the variation in the price coefficient, which incorporates scale. Further, it is assumed that any distribution of γ_n and η_n in equation 3.17 and 3.18 implies a distribution of γ_n and w_n in equation 3.19. Thus, the utility function becomes the utility in WTP space; allowing for the direct estimation of WTP estimates that is not skewed. Also, the WTP is said to be influenced by individual-specific variables which are those non-attribute-based factors that influence the willingness to pay margins of individual decision-makers, thus incorporation individual-specific variables into the WTP space model allow researchers to predict determinant of WTP.

3.13.6 Empirical Specification of WTP Space Model and its Determinants under the Mixed Logit Framework

The process followed the mixed logit model that allowed for the direct inclusion of the factors that influence farmers willingness to pay for improvement in the CSCES product attributes in the based model. To estimate the marginal WTP estimates and their determinants, utility in WTP space in Equation 3.19 was applied. The model was empirically specified as:

$$U_{nj} = \beta_0 - \beta_1 x_1 + (\beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5) w_n + \beta_{6-9} z_{1-4} + e_{nj};$$

$$\text{where } w_n = \beta_6 z_1 +, \ldots, +\beta_{20} z_{13} \qquad (3.20)$$

Where: U_{nj} = the utility function of the nth farmer; w_n = willingness to pay estimates; βs = unknown parameters to be estimated; e_{nj}= stochastic error term The independent variables are described in Table 3.4.

Table 3.4: Description of Variables in Equation 3.16 and 3.20

Variable	Description	Apriori
x_1	Price attribute of CSCES	-
x_2	Service accessibility attribute of CSCES	+
x_3	Service content attribute of CSCES	+
x_4	Service responsiveness attribute of CSCES	+
x_5	Service reliability attribute of CSCES	+
Z_1	Sex of farmer (dummy: 1 = male; 0 female)	+/-
Z_2	Age of the farmer in years	+
Z_3	Education (years spent in school)	+
Z_4	Farm income (estimated revenue from farm output)	+/-
Z_5	Perceived extension service quality with respect to the tangibility dimension *(measured on a continuous scale)*	+
Z_6	Perceived extension service quality with respect to the reliability dimension *(measured on a continuous scale)*	+
Z_7	Perceived extension service quality with respect to the responsiveness dimension *(measured on a continuous scale)*	+
Z_8	Perceived extension service quality with respect to the assurance dimension *(measured on a continuous scale)*	+
Z_9	Perceived extension service quality with respect to the empathy dimension *(measured on a continuous scale)*	+
Z_{10}	Perceived rainfall variability *(index score from 0 to 1 continuum)*	+
Z_{11}	Perceived temperature variability *(index score from 0 to 1 continuum)*	+
Z_{12}	Perceived adverse effect of climate change *(index score from 0 to 1 continuum)*	+
Z_{13}	access to credit (dummy; 1=Yes, 0=Otherwise)	+

Source: Inkoom (2019)

3.14 The Analytical Techniques and Modelling approach for Objective Three

The measurement of farm-level efficiency of production has become an important and effective indicator of performance evaluation. As such, objective three of the study sought to estimate the farm-level efficiency of production among cocoa farmers. Accordingly, three efficiency components were estimated: technical efficiency, allocative efficiency, and economic efficiency. The Stochastic Frontier Analysis approach was used to estimate and predict the farm-level efficiencies of cocoa farmers. The SFA modelling approach is detailed in Subsections 3.14.1 to 3.14.2 respectively. The prediction of the determinants of the technical, allocative, and economic efficiencies was implemented with the Heckit treatment effect model which is discussed in Subsection 3.16.2.2.

3.14.1 Theoretical Specification of the Stochastic Production and Cost Frontier Models

Stochastic frontier analysis (SFA) is an econometric technique for efficiency measurement. The fundamental idea of the SFA model is the introduction of a composite error term: purely random error term and an inefficiency term (Henningsen, 2019; Behr, 2015; Inkoom & Micah, 2017; Coelli *et al*., 2005). The stochastic frontier approach overcomes the assumption that any deviation from the efficient frontier is solely attributed to managerial or inefficiency effect. The current study follows the stochastic production and cost frontier techniques of the SFA method.

Stochastic Production Frontier Function for Estimating Technical Efficiency

In literature, the estimation of technical efficiency has followed the use of the stochastic frontier production model. The stochastic production frontier function as originally and independently proposed by Aigner, Lovell, and Schmidt (1977), and Meeusen and Van den Broeck (1977) following the input-output oriented framework, is specified as:

$$y_i = f(x_i, \beta) + \varepsilon_i; \{\varepsilon_i = v_i + u_i\} \Rightarrow y_i = f(x_i, \beta) + v_i - u_i \quad (3.21)$$

Where y_i denotes a vector of the output of the i^{th} production unit; x_i represents a vector of inputs quantities employed by the i^{th} production unit; β is a vector of unknown parameters to be estimated which defines the outputs elasticities and ε_i represents the composite error term (i.e., $\varepsilon_i = u_i + v_i$: where u_i captures the inefficiency effects, and v_i captures stochastic or random effects), and N indicates the total number of production units. The functional form of the stochastic production function is specified as:

$$In(y_i) = \beta_o + \sum_{i=1-N}^{N} \beta_i In(x_i) + v_i - u_i \quad (3.22)$$

Usually, Equation 3.22 follows a Cobb-Douglas or Translog functional form; the choice of which depends on conditions such as flexibility, linearity in the parameter, regularity, principle of parsimony and empirical suitability of the data. The stochastic component, v_i is assumed to exhibit the property of $iid \sim N(0, \sigma_v^2)$ and are also distributed independently of the inefficiency component, u_i. The u_i as a non-negative inefficiency effect is assumed to exhibit the property of $iid \sim N(u_i, \sigma^2)$. The stochastic production frontier function distinguishes the actual output $\{y_i = f(x_i, \beta) + v_i - u_i\}$ from the frontier output $\{y_i^* = f(x_i, \beta) + v_i; u_i = 0\}$. From the functional relationship between the observed output and frontier output, the technical efficiency level of the i^{th} production unit is specified as:

$$TE_i = \frac{y_i}{y_i^*} = \frac{x_i\beta + v_i - u_i}{x_i\beta + v_i} = exp(-u_i|\varepsilon_i) \quad (3.23)$$

From Equation 3.23, the TE is a function of the value of the inefficiency term, u_i. Thus, u_i accounts for the difference between the observed output and the frontier output. The prediction of u_i follows different distributional assumptions. However, the current study follows the truncated normal distribution as utilised by Battese and Coelli (1995) where $u_i \sim (u, \sigma_u^2)$. In general, the TE score is bounded between 0 and 1. If $TE = 1; \{i.e. u_i = 0\}$ the production unit is technically efficient—indicates that the production unit is producing on the frontier (i.e., $y_i = y_i^*$). If $TE = 0; \{i.e. u_i > 0\}$ the production unit is technically inefficient—indicates that the production unit is producing below the frontier or optimum potential. Following Battese and Corra (1977) the log-likelihood function can be parameterised in terms of σ^2 and γ. This parameterisation is expressed as: $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{\sigma^2} =$

$\frac{\sigma_u^2}{\sigma_v^2+\sigma_u^2}$. The γ parameter lies between 0 and 1. If $\gamma = 0$, then all deviations from the frontier is attributed to the noise effect. On the other hand, if $\gamma = 1$, then all deviations from the frontier is due to technical inefficiency. This property as noted by Coelli *et al*. (2005) is convenient for iterative optimisation routines as it permits the selection of a starting value by conducting a preliminary search over the unit interval. Thus, for $0 \leq \gamma \leq 1$, the variability in the output of the i^{th} production unit is characterized by the presence of both technical inefficiency and stochastic noise.

Stochastic Cost Frontier Function for Estimating Economic Efficiency

In literature, economic efficiency is interchangeably referred to as cost efficiency. As such, its estimation has followed the use of the stochastic cost frontier model. The stochastic cost frontier model assumes that the production units minimise cost, hence permitting the estimation of the economic characteristics of the production technology and economic efficiency (Henningsen, 2019; Behr, 2015; Coelli *et al*., 2005). Technically, the cost frontier is a self-dual of the production function. Thus, to derive cost frontier dual to the production frontier, the mathematical relation of the composite error term changes from $v_i - u_i$ to $v_i + u_i$. The implication of this is that the difference reflects how inefficiency increases the use of inputs or reduces the amount of output (Bogetoft & Otto, 2019). With this theoretical adjustment to the composite error term, the production frontier function becomes $y_i = f(x_i, \beta) + v_i + u_i$ with $u_i \geq 0$. The cost frontier dual function is thus specified as:

$$c_i = f(w_i, y_i, \beta) + \varepsilon_i; \text{ where } \varepsilon_i = v_i + u_i \tag{3.24}$$

where c_i stands for the minimum cost to produce output y_i and w_i represents a vector of input prices. The β denotes a vector of unknown parameters to be estimated. The u_i accounts for cost inefficiency and the v_i accounts for stochastic noise. The same distributional assumptions and properties of the composite error terms under the stochastic production frontier apply to the stochastic cost frontier.

For empirical soundness, it is often assumed that all production units face the same input prices. Hence, to be economically (cost) efficient, production units must be technically and allocatively efficient. Technically, the cost frontier function shows the minimum cost of producing the output combination y when the inputs prices w and the technology set T are given (i.e., $c(w, y) = min\{\, wx|(x, y) \in T\}$. With this, arriving at the cost-efficient output requires comparing the observed cost to the minimum cost. The economic efficiency of the production unit thus becomes:

$$EE = \frac{\text{minimum cost}}{\text{observed cost}} = \frac{c(w,y)}{c} = \frac{c(w,y)}{wx} \tag{3.25}$$

To align the economic efficiency to the stochastic frontier basis, it must be parameterized via the inefficiency term u_i and introduce a multiplicative error term. The economic efficiency as specified by Farrell (1957), therefore, becomes:

$$EE = \frac{c(w,y)e^{v}}{c} \frac{c(w,y)e^{v}}{f(wx)e^{v}e^{u}} = e^{-u} \tag{3.26}$$

Following Farrell, the economic efficiency score is bounded between 0 and 1. If $EE = 1; \{i.e. u_i = 0\}$ the production unit is considered economically efficient—indicates that the production unit is producing the maximum output from a minimum input cost combination. On the other hand, if $EE = 0; \{i.e. u_i > 0\}$ the production unit is said to be economically inefficient. This implies the production unit is not minimising cost in producing a given output. Following this, the stochastic cost frontier yields an economic efficiency score with a composite effect of cost of technical inefficiency and allocative inefficiency.

Estimation of Allocative Efficiency

When the dual cost frontier model is employed with allocative efficiency assumed, the estimated economic (cost) efficiency estimate can be decomposed into the cost of technical inefficiency and the cost of allocative inefficiency. Hence, as proposed by Farrell (1957), the allocative efficiency of the i^{th} production unit can be deduced from the multiplicative expression of economic efficiency in relation to technical efficiency and allocative efficiency as follows:

$$EE = TE \times AE, \Rightarrow AE = \frac{EE}{TE}; \ \{0 \leq AE \leq 1\} \tag{3.27}$$

From the above expression, AE picks a value that is bounded between 0 and 1. If $AE = 1; \{i.e. u_i = 0\}$ means that the i^{th} production unit or decision-making unit is allocatively efficient. On the other hand, if $AE = 0; \{i.e. u_i > 0\}$ the production unit is said to be allocatively inefficient in production.

3.14.2 Empirical Specification of the SFA Models for Estimating Efficiency of Production in Cocoa Production

In this study, the estimation of economic, technical, and allocative was premised on the duality concept of production and cost frontiers. The empirical application of the SFA models in literature has largely centred on the use of two functional forms: Cobb-Douglas functional form and Translog functional form respectively. In the literature, there is no concrete consensus on which among the two is better. It is often advised that the choice should rest on the suitability of the model to the dataset and consistency with the theoretical underpinnings of the research objective; taking into consideration their strengths and weaknesses (O'Donnell, 2018; Greene, 2007; Coelli *et al*., 2005; Kumbhakar & Lovell, 2003). For instance, the Cobb-Douglas functional form has received an extensive application in empirical literature because it has algebraic tractability and can explain the substitution between inputs (Reynès, 2017; Santias, Cadarso-Suarez, & Rodriguez-Alvarez, 2011). However, the major limitation of the Cobb-Douglas model is that it is a restrictive model (Pavelescu, 2011; Behr, 2015). Notably, the Translog function is a more flexible extension of the Cobb-Douglas function

(Henningsen, 2019; Coelli *et al*., 2005; Kumbhakar & Lovell, 2003; Greene, 2007). The Translog model also permits the assessment of the interactive effects between the inputs and how it impacts output level (Coelli *et al*., 2005; Kumbhakar & Lovell, 2003; Greene, 2007).

Despite these interesting strengths of the Translog model, its empirical application is tied to much caution because of its limitations. For instance, as a quadratic logarithmic model, it requires the estimation of many parameters, thus making the interpretation of results difficult. Furthermore, because of the inherent multicollinearity problem in the Translog model, the significance of the parameter estimates is much problematic. To overcome this potential shortfall of multicollinearity, the Cobb-Douglas function is considered much appropriate. Furthermore, under the Cobb-Douglas framework, other econometric estimation problems such as serial correlation and heteroscedasticity can be adequately and easily handled (Coelli *et al*., 2005; Kumbhakar & Lovell, 2003; Murthy, 2002). The Cobb-Douglas as a linear logarithmic function requires the estimation of a few parameters, hence making interpretation of results easier. In addition, the Cobb-Douglas function can handle multiple inputs in its generalised form.

As pointed out by Kumbhakar and Lovell (2003), the Translog functional form is not self-dual, hence its application in economic efficiency following the self-dual relationship between production and cost function is not theoretically appropriate. The self-duality of the Cobb-Douglas allows for the estimation and decomposition of economic efficiency into technical and allocative efficiency (Henningsen, 2019; Coelli *et al*., 2005; Kumbhakar & Lovell, 2003). Although the restrictive nature of the Cobb-Douglas function is of concern, it has largely been agreed in literature that due to its superior property of self-duality, the model does not sacrifice quality and accuracy of empirical efficiency (Vega-Cervera & Murillo-Zamorano, 2013; Harvie & Charoenrat, 2013). Taking into consideration the duality concept that underpins the estimation of economic efficiency, the Cobb-Douglas functional form under the maximum likelihood estimation approach was adopted for the empirical specification of the stochastic production frontier and cost frontier.

Motivation for the Choice of the Cobb-Douglas Functional Specification

In estimating stochastic frontier functions, it has been argued that the estimation approach must satisfy both theoretical and empirical soundness (Henningsen, 2019; O'Donnell, 2018; Heathfield, 2016; Coelli *et al*., 2005; Kumbhakar & Lovell, 2003). Following this, the self-duality assumption that underpins economic efficiency decomposition favours the Cobb-Douglas function as against the Translog function. For instance, when estimating economic efficiency from the cost function following the self-duality approach to decompose it into its respective efficiency components of Technical and Allocative, the Translog function compares to the Cobb-Douglas function gives inconsistent and biased efficiency estimates (Henningsen, 2019; O'Donnell, 2018; Heathfield, 2016; Kumbhakar & Lovell, 2003). This is because as pointed out by Kumbhakar and Lovell (2003), the Translog function is not self-dual and as such its application in economic efficiency estimation following the duality approach is not theoretically appropriate. Additionally, it is argued that if farm firms are assumed to be price takers in the output and inputs market, using the Translog function to estimate the cost function is inappropriate (O' Donnell, 2018). This thereby suggests that if one wants to estimate a Translog function as against the Cobb-Douglas function within the duality framework, then the assumption of the perfect competition needs to be relaxed.

In very production analysis, one property that is of key interest is the monotonicity property. However, if the Translog function is assumed for the cost function, then this requirement must be relaxed (Henningsen, 2019; O'Donnell, 2018; Coelli *et al*., 2005). Henningsen (2019) posited that often the monotonicity assumption is globally fulfilled for the Cobb-Douglas function, whilst in the Translog function it is often violated. Given this, I estimated the economic efficiency of cocoa farmers following the duality theorem, it became necessary to adopt the Cobb-Douglas function as it provides unbiased and efficient efficiency estimates consistent with the duality assumption than the other functional forms (Henningsen, 2019; O'Donnell, 2018; Coelli *et al*., 2005; Kumbhakar & Lovell, 2003). Accordingly, I estimated the stochastic production and cost frontier functions within the Cobb-Douglas functional framework. From the stochastic production frontier, I was able to determine the output elasticities of each production inputs as employed by the cocoa farmers. Afterwards, I followed the self-duality concept of the stochastic cost frontier model to decompose the economic efficiency estimate into its respective efficiency components of technical and allocative. The formal empirical specification of the Cobb-Douglas stochastic production and cost frontier models as applied in the study is explained below.

Technical Efficiency Measure Following the Cobb-Douglas Production Frontier

The Cobb-Douglas production frontier function for one output and k inputs as applied in this study is specified as:

$$Iny_i = \beta_0 + \beta_1 Inx_1 + \beta_2 Inx_2 + \beta_3 Inx_3 + \beta_4 Inx_4 v_i - u_i \qquad (3.28)$$

Where: y_i = quantity of cocoa output (kg/hectare); β = unknown parameters to be estimated; x_1= amount of labour employed (man-day/hectare); x_2 = quantity of fertiliser applied (kg/hectare); x_3 = quantity of agrochemical or pesticides applied (litres/hectare); x_4 = cost of capital inputs; v_i = stochastic or noise effect; and u_i=

inefficiency effect term. The scaling of all variables per hectare of land as applied specified in Equation 3.28 was to enable unbiased interfarm comparison and eliminates the effect size of land in efficiency and productivity differentials among farmers. In this study, it was expected that the input variables will exhibit a monotonically non-decreasing characteristic with respect to variation in the output variable.

Economic Efficiency Measure Following the Dual Cobb-Douglas Cost Frontier

The Cobb-Douglas cost frontier function for one output and k inputs with as applied in this study is specified as:

$$InC_i = \beta_0 + \beta_1 Inw_1 + \beta_2 Inw_2 +, \dots, + \beta_5 Iny + v_i + u_i \tag{3.29}$$

Where: c_i = minimum cost to produce output y_i (GH¢/hectare); β = unknown parameters to be estimated; w_1= labour cost (GH¢/hectare); w_2 = fertiliser cost (GH¢/hectare); w_3 = agrochemical cost (GH¢/hectare); w_4 = capital cost (GH¢/hectare); y_i = output value (GH¢/hectare); v_i = stochastic or noise effect; and u_i= inefficiency effect term. The scaling of all variables per hectare of land as applied specified in Equation 3.29 was to enable unbiased interfarm comparison and eliminates the effect size of land size on efficiency differentials among farmers. In the study, it was expected that both the inputs prices and output quantity will exhibit a monotonically non-decreasing characteristic.

Allocative Efficiency Measure

From the multiplicative relation between technical efficiency, allocative efficiency, and economic efficiency, the empirical estimation of allocative efficiency was estimated by taking the ratio of economic efficiency to technical efficiency. This is given as: $EE = TE \times AE \Longrightarrow AE = \frac{EE}{TE}$.

3.14.3 Drivers of Technical, Allocative, and Economic Efficiencies

The analysis of the drivers of technical, allocative, and economic efficiencies are incorporated into the Heckit treatment effect model. The empirical application of the model is expounded in Sub-section 3.16.2.2.

3.15 The Analytical Techniques and Modelling approach for Objective Four

Food security situation as livelihood indicator among farming households has become a topical issue in the global community to the point of becoming the second goal in the Sustainable Development Goals agenda. Given this, the current study sought to ascertain and characterise the food (in)security situation of cocoa farmers in Ghana. The study, therefore, utilised the multidimensional food security framework to estimate and characterise the household food security of cocoa farming households in Ghana. Farmers were then categorised into four food (in)security groups. The modelling approach is detailed in Subsections 3.15.1.

3.15.1 Empirical Estimation of Household Food Security using a Multidimensional Food Security Index approach

Following the principles of experiential evaluation, a self-assessment item response instrument was used to collect data on the four dimensions of food security (i.e., Availability, Accessibility, Utilisation and Stability). Farmers responded to the instrument on both dichotomous and polytomous scales and their responses were organised to compute Household Food Security Index (HFS index) for each of the individual food security dimensions following Equation 3.30.

$$HFI\ index = \frac{x_{\text{actual}} - x_{\text{expected minimum}}}{x_{\text{expected maximum}} - x_{\text{expected minimum}} \tag{3.30}$$

The conceptual approach to Equation 3.30 follows the Human Development Index axioms promulgated by the UNDP as discussed in Equation 3.2 under section 3.13.1 (page, 65). Equation 3.30 gave an index score of 0 to 1, where 0 means food insecured and 1 means food secured. A movement from 0 to 1 implies increasing household food security, hence decreasing vulnerability to household food insecurity. The reverse movement from 1 to 0 implies increasing vulnerability to household food insecurity, hence decreasing household food security. Based on the HFS index obtained, households were classified into four main groups as showed in Table 3.5 by the quarterisation of the estimated HFS index.

Table 3.5: Household Food Security Categorisation

HFS index	Scoring	Classification
0.00 – 0.25	1	food insecured
0.26 – 0.50	2	Marginally food insecured
0.51 – 0.75	3	Marginally food secured
0.76 – 1.00	4	food secured

Source: Inkoom (2019)

Measuring Household Food Security using the Food Availability Dimension Approach

Following the idea of healthy food availability, the food consumption score (FCS) tool was used to generate a proxy measure for household calorie availability to represent food security in relation to the food availability dimension. Farmers were asked to indicate the various types of food items available to the household over the past 7 days. The identified food items were then grouped and assigned caloric weighted as developed by the World Food Programme standardized food group weighting scheme. The weighting process is as follows; grains and cereals--assigned a weight of 2; roots, tubers, and plantain--assigned a weight of 2; fruits--assigned a weight of 1; meat, fish, and egg--assigned a weight of 4; dairy products--assigned a weight of 4; fats and oils--assigned a weight of 0.5; vegetables--assigned a weight of 1; nuts and legumes--assigned a weight of 3; and bakery products and beverages--assigned a weight of 0.5 (World Food Programme, 2012). Based on this, the total number of food items available at each household was multiplied by the weight score and the total summed to generate an overall household caloric intake. From data collected a given household was expected to have a potential caloric score ranging from 4 to 77. Where the score of 4 suggests that at worst it was expected every farm household would at least have a grain or tuber product available. Following the HFS index specified in Equation 3.40, the household food security with respect to the availability dimension was computed. The details of the food availability item that went into the food availability component are presented under part four of the structured interview schedule presented in Appendix 1.

Measuring Household Food Security using the Food Accessibility Dimension Approach

The study employed the Household food insecurity access scale (HFIAS) containing a set of nine generic questions that better represent a universal domain of the accessibility dimension of food security (FAO, 2014). This was employed at the frequency of occurrence level. Farmers were asked to score the frequency of occurrence of the food accessibility condition on a scale of four-point scale (where; 0 means never, 1 means rarely, 2 means sometimes and 3 means often). Based on the score assign, a household food insecurity access score was generated for each household by summing up the frequency of occurrence codes. Mathematically, a continuous measure gives a low score of 0 (i.e., 0 x 9 item responses) and a high score of 27 (i.e., 3 x 9 item responses). The higher the score the higher the probability of a household being vulnerable to food insecurity with respect to accessibility. Following the HFS index specified in equation 3.40, the household food security with respect to the accessibility dimension was computed. The HFS index obtained under this framework was then subtracted from 1 to align it to the argument of household vulnerability to food insecurity. The details of the HFIAS items that went into the food accessibility dimension is presented in part four of the structured interview schedule presented in Appendix 1.

Measuring Household Food Security using the Food Utilisation Dimension Approach

The Household Dietary Diversity scale (HDDS) was employed to estimate household food security status regarding food utilisation. The HDD tool indicates the total number of different foods or food groups consumed by the household over a given reference period which then acts as a proxy indicator of the nutritional quality and thus, the food utilisation dimension of food security (FAO, 2017; Berry *et al*., 2015; Maxwell *et al*., 2014; World Food Programme, 2012). Farmers were asked to indicate the variety of food items consumed within the last 24 hours. Food items consumed by farmers within the reference period were then classified under nine food groups in Ghana (fruits; vegetables; fish and meat; milk and egg; nuts and legumes; roots, tubers, and plantains; grains and cereal; fats and oils; and bakery products and beverages). The food grouping was based on their nutritional functions, based on which farm households were assigned a dietary diversity score of 1 to 9, depending on the total count of food groups found in their dietary consumption (Hussein *et al*., 2018; FAO, 2017; Berry et al., 2015; World Food Programme, 2012). The dietary diversity score was then scaled using the World Food Programme caloric weighting scheme (World Food Programme, 2012). Following the HFS index specified in Equation 3.40, the household food security with respect to the utilisation dimension was then computed. The details of the HDD items that went into the food utilisation component are presented under part four of the structured interview schedule presented in Appendix 1.

Measuring Household Food Security using the Food stability or vulnerability Dimension Approach

In measuring household food stability, the study adopted the Household Coping Strategy Index (HCSI) measure of household food insecurity. The HCSI incorporates vulnerability elements of food insecurity as well as the deliberate actions of households when faced with food insufficiency (Ibok, Osbahr, & Srinivasan, 2019; FAO, 2017; World Food Programme, 2012). That is, the HCSI is a tool used to evaluate how households manage to get enough food for consumption in the face of persistent food or economic resource deficit (Ibok, Osbahr, & Srinivasan, 2019; Perez-Escamilla, Gubert, Rogers, & Hromi-Fiedler, 2017; FAO, 2017; World Food Programme, 2012). The HCSI instrument was used to identify the various coping strategies adopted by farmers during persistent food and economic resource deficit. Afterwards, farmers were asked to assign a score of 1 to 10 depicting the frequency of use of each strategy by the household. Intuitively, the frequency score also indicates how frequent farmers run out of food and economic resources, hence depicting their vulnerability to food insecurity. This thus, suggests that the higher the frequency score, the higher the severity of food insecurity condition. Following the HFS index specified in Equation 3.40, the household food security with respect to the stability dimension was computed. The HFS index obtained under this framework was then subtracted from 1 to align it to the argument of household vulnerability to food insecurity. The details of the HCSI items that went into the coping strategy scale are presented under part four of the structured interview schedule presented in Appendix 1.

Estimation of Composite Multidimensional Household Food Security Index (MHFS index)

The composite multidimensional household food security index (MHFS index) for individual farmers were estimated from the summated mean score value from the parameter estimates from the application of the HFS index model to the four food security dimensions (i.e., $MHFS_{index} = (\sum_{n=1}^{n} HFS_{index})/n$). The grouping of farmers into their respective categories of food security situation follows what is presented in Table 3.5. Having estimated the HFS index for each of the food security dimensions (i.e., availability, accessibility, utilisation, and stability) and the composite household food security index, the study went further to compute a household food insecurity vulnerability index (HFIV index), by subtracting the HFS index from one (i.e., HFIV index = 1 - HFS index). This was aimed at assessing the probability of farmers facing a severe food insecurity situation in the medium-to-long term. The estimated HFIV index at the dimension level was then used to generate a composite multidimensional food insecurity vulnerability index (MHFIV index).

The Alkire-Foster percentage contribution estimation approach was then followed to estimate the percentage contribution of each dimension to the multidimensional food insecurity vulnerability index (Alkire & Foster, 2011a, b). The estimation approach is given as $[(w_{hf}HFIV_{hf})/MHFIV_{hf})) * 100]$: where w_{hf} represents a weighting score; $HFIV_{hf}$ represents the dimension level food insecurity vulnerability index; $MHFIV_{hf}$ represent the multidimensional food insecurity vulnerability index which indicates farmers vulnerability to food insecurity at the aggregate level. In the estimation process, an equal weighting index of 1/4 (i.e., 0.25) was assigned to each of the four dimensions. To validate whether the approach used in measuring food security matters or not (i.e., unidimensional against multidimensional approach), an ANOVA test was carried out. Here, it was assumed that there is no significant mean difference among the HFI index from the four food security dimensions (i.e., the approaches do not matter, hence one could use a unidimensional approach to appropriately capture the food security situation of farmers instead of a multidimensional approach).

3.16 The Analytical Techniques and Modelling approach for Objective Five

This objective is assumed to be the anchor of the study. The objective sought to explore the causal relationship between extension service quality, CSA and efficiency of production and food security status among cocoa farming households. To this, the endogenous treatment effect model (Heckit treatment effect model) was employed as an analytical tool. Furthermore, the structural equation model was used for the confirmatory analysis of the sequential causal relationship outcome from the Heckit treatment effect model. This was done by bringing the four key constructs, extension service quality, adoption of CSA practice, efficiency of production, and food security status under a single modelling framework. The modelling approach is detailed in Subsections 3.16.1 to 3.13.4 respectively.

3.16.1 Theoretical Specification of Heckit Treatment Effect Model

The Heckit treatment effect model offers practical solutions to various types of endogenous treatment effect evaluation problems by isolating the effect of a treatment variable (t) on an outcome variable (y). The model unlike the standard Heckman selection model presents the opportunity for analysing outcome data observed for both $y = 1$ and $y = 0$ in an evaluation and observational study. The model as a counterfactual framework allows for the modelling of the impact of an endogenous treatment variable on an outcome variable which is also influenced by observable and unobservable factors. For example, assessing the impact of the adoption of climate response technology on farm productivity presents some challenges due to the possible effect of self-selectivity and endogeneity problems. In this example, assuming the use of climate response technology be the treatment variable (t) and farm productivity as the outcome variable (y), conditioned on the occurrence of climate change (Δ); then using the OLS regression to estimate the causal inference would lead to biased and inefficient estimation.

The Heckit endogenous treatment effect invokes a requirement that allows for relating the outcome unobservable to the choice of treatment, thereby correcting the self-selectivity and endogeneity problem in the estimation of the direct effect of the treatment variable on the outcome variable (Scott, 2019). For instance, if unobserved characteristics of farmers differentially influence those who use the climate response technology and those who do not; then it makes sense to let unmeasured variance vary depending on whether a farmer enters the treatment or not (i.e., uses the climate response technology or not). Conceptually, the outcome expectation within this framework given the treatment (t), observable determinates of the outcome variable (x) and determinates of treatment variable (z), unobservable influences on the outcome (u_y), and unobservable influence on treatment variable (u_v); conditioned on the occurrence of climate change (Δ) is expressed as:

$$E(y_1|x,z,t=1)|\Delta = \mu_1(x) + E(u_1|x,z,t=1)|\Delta \tag{3.31}$$

$$E(y_0|x,z,t=0)|\Delta = \mu_0(x) + E(u_0|x,z,t=0)|\Delta \tag{3.32}$$

To account for the endogeneity problem, a control function (k) is introduced to model endogeneity into the residual terms of the outcome model to control for bias taking into consideration the propensity (P) of being selected into the treatment. With this, the outcome expectation can be recast as follows:

$$E(y_1|x,z,t=1)|\Delta = \mu_1(x) + k(P(x,z))|\Delta \tag{3.33}$$

$$E(y_0|x,z,t=0)|\Delta = \mu_0(x) + k(P(x,z))|\Delta \tag{3.34}$$

Equations 3.31 to 3.34 indicate a more general approach to selection and endogeneity bias where selection into treatment is due to both observable and unobservable factors. This implies that once we account for the influences of (z) and (x) on selecting into the treatment (i.e., use of climate services) and outcome (farm productivity), then any remaining unobserved factors are incorporated into the evaluation of the use of climate service on farm productivity. With this, the Heckit treatment effect model can efficiently incorporate selection on the unobservable and the observable. Stemming from this, the selection and error covariance terms are stated as follows: $Cov(u_y, u_v) \neq 0$, $Cov(z, u_y) \neq 0$, and $Cov(z, u_v) \neq 0$. This allows for the unobserved factors on the outcome and unobserved factors on treatment to be related $[Cov(u_y, u_v)]$, as well as an observed factor on treatment and unobserved factors on the outcome to be related $[Cov(z, u_y)]$, and observed and unobserved factors of treatment to be related $[Cov(z, u_y)]$.

The functional specification of the Heckit endogenous treatment effect model used to estimate the direct causal effect of the endogenous treatment variable (t) on the outcome variable (y), conditioned on the occurrence of climate change (Δ) is mathematically formulated as follows:

$$y_j|\Delta = f(x_j\beta, \delta t_j, u_{yj}|\Delta) \Rightarrow y_j|\Delta = x_j\beta + \delta t_j + u_{yj}|\Delta \qquad (3.35)$$

Situating Equation 3.35 in the stated example given above, the equation defines the likelihood that a farming household will attain a high increase in farm productivity (y_j) given the onset of climate change depends on the use of climate advisory service and other farmer-specific characteristics and measures undertaken to achieve it in the presence of climate change. In the above equation, δ defines the odds of being selected into the treatment (t_j). Furthermore, the t_j is conceptualised as resulting from a latent variable (t_j^*) which accounts for both observed and unobserved influences on selection into treatment and whose linear function is expressed as

$$t_j^* = z_j\gamma + u_{vj}|\Delta \qquad (3.36)$$

where:

$$t_j = \begin{cases} 1, \text{ if } t_j^* > 0 \\ 0, \text{ otherwise} \end{cases} \tag{3.37}$$

Theoretically, in the application of Equations 3.35 and 3.36, it is assumed that $u_{yj} \sim N(0, \sigma^2)$ and $u_{vj} \sim N(0,1)$, with the $\rho = cov(u_{yj,} u_{vj})$. According to Greene (2012), ρ is not directly estimated. The direct estimates are $In(\rho)$ and $ArcTanh(\rho) = \tau$; where the inverse hyperbolic expression is given as $\tau = 1/2In[(1+\rho)/(1-\rho)]$. Following an inverted approach to the inverse hyperbolic tangent expression, ρ can now be directly expressed as $\rho = [exp(2\tau) - 1]/[exp(2\tau) + 1]$. The relevance of ρ under the Heckit treatment effect method is that, ρ serves to indicate the extent to which sample selectivity is of concern and as such establishes the value reflected in δ. If $\rho = 0$, then there is no evidence of selectivity and endogeneity problem, and thus, the treatment effect model then reduces to the OLS estimate. Furthermore, ρ helps to test the appropriateness and fit of the Heckit treatment effect model to the data. It tries to establish whether there exists a treatment effect relationship between the treatment model and the outcome model. To avoid bias estimation, the Heckit treatment effect model assumes that the degree of correlation (ρ) between the two-error term is non-zero. As such a test of $\rho(H_0: \rho = 0)$ is performed to evaluate whether the joint likelihood of the selection equation (probit model) and the outcome equation (regression model) on the data against the treatment effect model is likely to ensure that $\rho \neq 0$. If the estimated rho is found to be non-zero, we reject the null hypothesis and conclude that rho is not equal to zero. This suggests that the use of the treatment effect model is appropriate and thus fits the data well.

3.16.2 Empirical Specification of the Heckit Treatment Effect Model

The study hypothesised that there is a direct and indirect relationship between extension service quality, CSA, economic efficiency, and food security. This relationship is conditioned on the two basic preconditions: climate change awareness (CH^{Δ} = captured by perceived rainfall variability, perceived temperature variability, perceived adverse effect of climate change, awareness of CSA options as adaptation response; and perceived risk associated with investing in CSA) and access to extension service (ϖ =captured by frequency of extension contact and quality extension service). As illustrated in the conceptual framework in Figure 2.2, there is a hypothesized sequential causal link effect of extension service quality on the adoption of CSA practice which subsequently impacts farm-level efficiency and the food security status of cocoa farming households under a transitivity rationale. To be able to isolate and predict the individual effects of extension service quality, adoption of CSA practices and farm-level efficiency on the food security status of cocoa farming households, the Heckit endogenous treatment effect model was employed. Empirically the Heckit treatment effect model as applied in this study is given as:

$$y_j|CH^{\Delta},\varpi = f(x_j, \beta, \delta t_j, \varepsilon_j|CH^{\Delta},\varpi) \tag{3.38}$$

Where: y_j represents the outcome variables; t_j represents the treatment variable; $\beta, \delta,$ and ε are unknown parameters to be estimated; x_j denote socioeconomic explanatory variables; CH^{Δ} denotes climate change awareness indicators and ϖ denotes extension service access indicator. The actual estimation of equation 3.38 was done in three sequential settings following the conceptual framework and is discussed in Sub-sections 3.16.2.1 to 3.16.2.3.

3.16.2.1 Estimating The Direct Causal Effect of Extension Service Quality on the Adoption of CSA Practices

Generally, extension service is considered as an essential institutional indicator variable with a higher propensity of significantly influencing the adoption decision-making behaviour of farmers. The study argues that increasing access to extension service does not necessarily translate into positively influencing farmers' adoption decision-making behaviour per se but rather the quality of the service delivered. This is because service quality builds trust in service users (Unidha, 2017; Eisingerich & Bell, 2008; Setiawan & Sayuti, 2017), and this triggers a higher likelihood of choosing to practice technologies introduced to them by the service providers. The study assumed that how farmers perceived the quality of extension service, accounts for the possible differential in the adoption of CSA practice. Hence, perceived extension services quality and the adoption of more CSA strategies is a simultaneous decision process. Accordingly, it was assumed that the likelihood that a farmer will adopt more of the CSA options given the occurrence of climate change $(CH^{\Delta})$and access to extension (ϖ) depends on the quality of extension service received and other socioeconomic characteristics. To validate this assertion, the Heckit treatment effect model as specified in equation 3.38 was applied as follows:

$$y_{CSA_j}|CH^{\Delta} = \beta_o + \beta_1 t_{ESQ_J} + \beta_2 CH_j^{rain} + \beta_3 CH_j^{temp} + \beta_4 CH_j^{cmpat} + \beta_5 CH_j^{acsa} + \beta_6 CH_j^{rcsa} + \beta_{7-13} x_{j(1-7)} + \varepsilon_j \quad \text{where;} \tag{3.39}$$

$$t_{ESQ_J}|\varpi = \beta_0 + \beta_1 \varpi_j + \beta_{2-8} x_{j(1-7)} + u_j$$

Where y_{CSA_j}denotes the outcome variable, adoption of CSA practice (total count of CSA options currently practised by the jth farmer); t_{ESQ_J} denote the treatment variable, extension service quality—takes the value 1 for farmers who perceived the service quality to be high (i.e., above-average service quality perception score) and 0 for those who think otherwise (i.e., below average service quality perception score); x_j denotes farmer-specific variables; CH^{Δ} denotes climate change indicators; ϖ denotes access to extension service indicator; the βs are unknown parameters to be estimated; ε_j and u_j denotes the two error terms for the outcome model and the treatment model. The splitting of the farmers into treatment groups based on their perceived extension quality score followed the binomial distribution theorem or the bivariate normality using the sample mean of the perceived extension quality index as the threshold. The explanatory variables that went into Equation 3.39 are explained as follows:

Table 3.6: Description of Explanatory Variables for Heckit Treatment Effect Model under Section 3.16.2.1

Variable	Description	Apriori
CH_j^{rain}	perceived rainfall variability	+
CH_j^{temp}	perceived temperature variability	+
CH_j^{cmpat}	perceived adverse effect of climate change	+
CH_j^{acsa}	Awareness of CSA option as adaptation response	+
CH_j^{rcsa}	Perceived risk associated with investing in CSA	-
ϖ_j	Frequency of extension contact	+
x_1	sex of farmer *(1 = male, 0=female)*	+/-
x_2	Age of farmer in years	+
x_3	Education level *(years spent in school)*	+
x_4	Years of farming experience	+
	Table 3.6 Cont.	
x_5	access to credit (1=Yes, 0=Otherwise)	+
x_6	farmer-based organisation *(1 =member, 0= Otherwise)*	+
x_7	Farm income (Gh¢)	+

Source: Inkoom (2019)

3.16.2.2 Estimating the Direct Causal Effect of CSA on Farm-Level Efficiency (Economic, Technical, and Allocative)

The increasing trend of climate change (including climate variability and extremes) present a serious threat to farmers. This is because, the situation increases their exposure and vulnerability to climate risk effects such as low productivity, yield loss, food insecurity among others. Literature suggests that the adoption of climate smart adaptation practices provide productivity cushioning to farmers by reducing exposure and vulnerability to climate risk (Otitoju, 2015; Ehiakpor *et al.*, 2016; Roco, Bravo-Ureta, Engler, & Jara-Rojas, 2017). Adaptation to climate change is important in engineering sustainable agricultural productivity growth (Otitoju, 2015; Nguyen, 2014; IPCC, 2014; Roco *et al.*, 2017). In production economics, efficiency estimate represents the most rigorous measure of farm performance and productivity (Bogetoft & Otto, 2019; Henningsen, 2019; Rasmussen, 2011; Inkoom & Micah, 2017).

Accordingly, the study assumed that the likelihood that a farmer will attain a higher efficiency level given the onset of climate change and access to extension is dependent on the adoption of CSA and other socioeconomic factors in the presence of climate change. To ascertain this claim, the Heckit treatment effect model as specified in equation 3.38 was applied as follows:

$$y_{EFF_j}|CH^{\Delta},\varpi = \beta_o + \beta_1 t_{CSA_J} + \beta_2 CH_j^{cmpat} + \beta_3 CH_j^{acsa} + \beta_4 CH_j^{rcsa} + \beta_5 \varpi_{ESQ_j} + \beta_6 \varpi_{FEC} + \beta_{7-14} x_{j(1-8)} + \varepsilon_j \quad \text{where;} \tag{3.40}$$

$$t_{CSA_J}|CH^{\Delta} = \beta_0 + \beta_1 CH_j^{cmpat} + \beta_2 CH_j^{acsa} + \beta_3 \varpi_{FEC} + \beta_{4-6} x_{j(1-3)} + u_j$$

Where y_{EFF_j} denotes the outcome variable, efficiency of production (economic efficiency, technical efficiency, and allocative efficiency of the jth farmer); t_{CSA_J}denote the treatment variable, adoption of CSA practice—takes the value 1 farmers whose total count of CSA options adopted is above the sample average (above average adapters) and 0 for those whose total count of CSA options adopted is below the sample mean (i.e., below average adapters); x_j denotes farmer-specific variables; CH^{Δ} denotes climate change indicators; ϖ denotes access to extension service indicator; the βs are unknown parameters to be estimated; ε_j and u_j denotes the two error terms for the outcome model and the treatment model. The splitting of the farmers into treatment groups based on the total count of CSA strategies currently adopted by farmers followed the binomial distribution theorem or the bivariate normality using the sample CSA adoption mean as the threshold. The explanatory variables that went into Equation 3.40 are explained as follows:

Table 3.7: Description of Explanatory Variables for Heckit Treatment Effect Model under Section 3.16.2.2

Variable	Description	Apriori
CH_j^{cmpat}	perceived adverse effect of climate change	+
CH_j^{acsa}	Awareness of CSA option as adaptation response	+
CH_j^{rcsa}	Perceived risk associated with investing in CSA	-
ϖ_{ESQ}	Access to quality extension service	+
ϖ_{FEC}	Frequency of extension service	+
x_1	sex of farmer *(1 = male, 0=female)*	+/-
x_2	Age of farmer in years	+
x_3	Education level *(years spent in school)*	+
x_4	Years of farming experience	+
x_5	access to credit (1=Yes, 0=Otherwise)	+
x_6	farmer-based organisation *(1 =member, 0= Otherwise)*	+
x_7	Land size (*hectares*)	+
x_8	Farm income (Gh¢)	+

Source: Inkoom (2019)

3.16.2.3 Estimating the Direct Effect of Farm-Level Efficiency (Economic, Technical, and Allocative) on Food Security

The philosophical position of this study is that if the hypothesised relationships as presented in the conceptual framework in Figure 2.2 stand, then it can be implied that extension service quality, adoption of CSA practices will affect food security via their link effect on farm-level efficiency, all other things being equal. Generally, improved farm-level efficiency would generate higher farm output and income for farm households. Higher farm output and income would consequently increase the availability, accessibility, utilization, and stability of the food, thereby improving household food security conditions. Following the conceptual framework, the study assumed that the likelihood that a farmer will attain higher food security status given the onset of climate change depends on the efficiency of production, access to quality extension service, adoption of CSA technologies and other socioeconomic factors in the presence of climate change. Accordingly, to estimate the direct effect of farm-level efficiency (i.e., economic, technical, and allocative) on food security the Heckit treatment effect model as specified in equation 3.38 was applied as follows:

$$y_{HFS_j}|CH^{\Delta},\varpi = \beta_o + \beta_1 CH_j^{ucsa} + \beta_2 t_{EFF_J} + \beta_3 \varpi_{ESQj} + \beta_{4-14} x_{j(1-10)} + \varepsilon_j$$

where; $t_{EFF_J}|CH^{\Delta},\varpi = \beta_0 + \beta_1 CH_j^{ucsa} + \beta_2 \varpi_{ESQj} + \beta_{3-12} x_{j(1-10)} + u_j$ (3.41)

Where y_{HFS_j} denotes the outcome variable, household food security status; t_{EFF_J} denote the treatment variables, economic efficiency, technical efficiency, and allocative efficiency of the jth farmer—takes the value 1 for farmers whose efficiency score is above the sample mean (i.e., above-average efficiency score) and 0 for those whose efficiency score is below the sample mean (i.e., below-average efficiency score); x_j denotes farmer-specific variables; CH^{Δ} denote climate change indicators; ϖ denotes access to extension service indicator; the βs are unknown parameters to be estimated; ε_j and u_j denotes the two error terms for the outcome model and the treatment model. The splitting of the farmers into treatment groups based on the farm-level efficiency distribution followed the binomial distribution theorem or the bivariate normality using the sample mean efficiency as the threshold. The explanatory variables that went into equation 3.41 are explained as follows:

Table 3.8: Description of Explanatory Variables for Heckit Treatment Effect Model under Section 3.17.2.3

Variable	Description	Apriori
CH_{ucsa}^{Δ}	Adoption CSA technologies	+
ϖ_{ESQ}	Access to quality extension service	+
ϖ_{FES}	Frequency of extension contact	+
x_1	sex of farmer *(1 = male, 0=female)*	+/-
x_2	Age of farmer in years	+
x_3	Education level *(years spent in school)*	+
x_4	Years of farming experience	+
x_5	access to credit (1=Yes, 0=Otherwise)	+
x_6	farmer-based organisation *(1 =member, 0= Otherwise)*	+
x_7	Land size (*hectares*)	+
x_8	Farm income (Gh¢)	+
x_9	Off-farm economic engagement *(1=yes, 0=otherwise)*	+
x_{10}	household size	+

Source: Inkoom (2019)

3.16.3 Theoretical Specification of Structural Equation Model (SEM): The PLS-SEM approach

Structural equation modelling uses a system of simultaneous equations to represent, estimate, and test a network of relationships between manifest/observed variables and latent/unobserved variables. SEM assumes multivariate normality rather than a normal distribution and provides a general framework for the linear modelling of multifaceted relationships (Ravand & Baghaei, 2016; Monecke & Leisch 2012; Tenenhaus, Vinzi, Chatelin, & Lauro, 2005). As noted by Schumacker and Lomax (2004), the goal of SEM analysis is to determine the extent to which the theoretical model is supported by sample data. SEM is considered a more robust approach to testing substantive theories as it can combine factor analysis and regression (Ravand & Baghaei, 2016; Zainol, 2016). SEM is more flexible and offers accurate treatments of measurement errors (Ravand & Baghaei, 2016; Schumacker & Lomax, 2004). Two main approaches to SEM have dominated the literature and these are the covariance-based SEM (CB-SEM) and the partial least square SEM (PLS-SEM). CB-SEM is a parametric approach requiring distributional assumption and large sample size, whereas PLS-SEM is a variance-based and nonparametric approach that makes no distributional assumptions and can be estimated with a small sample size (Ravand & Baghaei, 2016; Schumacker & Lomax, 2004; Bollen & Noble, 2011; Zainol, 2016). Furthermore, CB-SEM is appropriate for theory testing and applicable in domains with the existence of substantive knowledge and theoretical foundations, whereas PLS-SEM is more suitable for exploratory research and theory building or an extension of existing structural theory (Zainol, 2016; Sanchez, 2013; Monecke & Leisch 2012). Despite this, it is agreed in literature that CB-SEM and PLS-SEM are complementary rather than competitive, thus their choice should be founded on the research context and the objectives (Chin, 2010; Ravand & Baghaei, 2016; Hair, Hult, Ringle, & Sarstedt, 2017).

In literature, the theoretical specification SEM follows two main directions: reflective mode and formative mode. In the reflective mode, the latent variable is considered as the cause of the manifest variables, whereas in the formative mode the manifest variables are the cause of the latent variable (Sanchez, 2013; Hair *et al.*, 2017). The specification of SEM usually consists of two basic models: the measurement model (outer model) and the structural model (inner model). The measurement model relates observed variables to their respective latent variables. The structural model relates the latent variables with each other according to the hypothesized theory. Following the PLS-SEM approach, the structural and measurement models with a weighting scheme in a matrix notation can be presented as

Structural model: $\eta_i = \beta_0 + \beta\eta_i + \varepsilon_i$ (3.42)

Measurement model: $\eta_i = \delta_0 + \delta\kappa_i + e_i$ (3.43)

Weighting scheme: $w_i = \pm\,[cor(\eta_i, \kappa_i)]$ (3.44)

The theoretical explanation of the variables η_i in the structural and measurement models denote the latent variables (both endogenous and exogenous). In the measurement model κ_i denotes the manifest variables (all exogenous). The β and δ represent path coefficients (factor loading) and regression coefficients respectively. The ε_i and $e_i$denote the error terms which are assumed to be uncorrelated with each other and with κ_i. The weighting scheme helps to bridge the gap between the virtual latent variable and the material latent variable (Sanchez, 2013; Wold 1982; Lohmoller, 1989).

3.16.4 Empirical Specification of SEM for testing the Implication of the Heckit Treatment Effect Model Results

Here, the interest is to test the implication of the Heckit treatment effect model results by focusing on the inner or structural component of the SEM equation. Following the formative mode of PLS-SEM specification, the SEM equation as applied in this study is specified as:

Structural model (inner or latent variable model)

$$\eta_{FSS} = \beta_0 + \beta_1\eta_{EE} + \beta_2\eta_{CSA} + \beta_3\eta_{ESQ} + \varepsilon_i \quad (3.45)$$

Measurement model (outer or manifest variable model):

$$\eta_{FSS} = \beta_0 + \beta_1 FAV + \beta_2 FAS + \beta_3 FUT + \beta_4 FSB + e_i \quad (3.46)$$

$$\eta_{EE} = \beta_0 + \beta_1 TE + \beta_2 AE + e_i \quad (3.47)$$

$$\eta_{CSA} = \beta_0 + \beta_1 CD + \beta_2 PIV + \beta_3 PA + \beta_4 FA + \beta_5 OFD$$
$$+ \beta_6 CPD + \beta_7 STM + \beta_8 NCD + e_i \quad (3.48)$$

$$\eta_{ESQ} = \beta_0 + \beta_1 TA + \beta_2 RB + \beta_3 RP + \beta_4 AS + \beta_5 EM + e_i \quad (3.49)$$

Where: η denotes the matrix of latent variables (ESQ—Extension service quality, CSA—climate smart adaptation, EE—economic efficiency and FSS—food security score); κ denotes the matrix of manifest variables (TA—tangibility, RB—reliability, RS—responsiveness, AS—assurance, and EM—empathy representing service quality indicator; CD—crop diversification, PIV—improved crop varieties, PA—optimal pesticides application, FA—optimal fertiliser application, CPD—changing planting dates, OFD—off-farm diversification, STM—shade tree management, and NCD—non-crop diversification representing indicators for use of CSA practices; TE—technical efficiency and AE—allocative efficiency denoting efficiency of production indicators; and FAV—food availability index, FAS—food accessibility index, FUT—food utilisation index, and FSB—food stability index representing household food security indicators); βs are unknown parameters to be estimated representing path coefficients (factor loadings) and regression coefficients respectively. In addition, ε_i and e_i denote the error terms.

3.17 Summary Statistics of Cocoa Farmers-specific Characteristics of Cocoa Farmers

This section presents summary statistics that gives descriptive scenario on selected farmer-specific characteristics of the sampled population. The results are accordingly presented in Table 3.9. The results as indicated in Table 3.9, reveal that the majority (i.e., 67.2%) of the farmers interviewed were males. This portrays that the cocoa farming business in Ghana is largely male-dominated. One possible reason that could account for this is that in Ghana women are largely found in food crop production, leaving the cash crop production to men. The age distribution of the farmers interviewed ranged from 30 years to 87 years with a mean of approximately 47 years and a standard deviation of 11 years.

Table 3.9: Descriptions of Farmer-specific Characteristics

Continuous Variable		Mean	Sd	Min	Max
Age		47	11	30	87
Household size		5	2	1	12
Years of education		9	5	0	18
Years of farming experience		18	9	10	60
Frequency of extension contact per period		7	1.9	5	13
Land size in hectares		5.1	1.8	2.0	8.0
Labour use (man-day/ha)		82	37	41	182
Fertiliser application (kg/ha)		199	41	150	250
Agrochemical application (Litre/ha)		2	1	1	5
Capital (GH¢/ha)		507	159	186	862
Quantity of farm output per hectare (Kg/ha)		874	90	750	1000
Categorical variable	**Category**		**Frequency**		**Percentage**
Sex	Male		484		67.22
	Female		236		32.78
Educational level	No formal education		149		20.69
	Primary level		173		24.03
	Junior Secondary		266		36.94
	Senior Secondary		105		14.58
	Tertiary		27		3.76
Land ownership title	Own land		364		50.56
	Family land		218		30.28
	Leased land		138		19.16
Membership to FBO	Yes		375		52.08
	No		345		47.92
Off-farm economic engagement	Yes		367		50.97
	No		353		49.03

Source: Field Survey, Inkoom (2019) n = 720

This demonstrates that the average cocoa farmer is within the active working-age group of the labour force as suggested by the Ghana Statistical Service Labour force categorisation. Comparing to the 60-year age threshold for active economic engagement, it can be deduced that the average farmer has about 13 years of active working years ahead of him/her. All other things being equal, it can thus be inferred that the average farmers can still contribute positively to the growth of the cocoa industry in terms of productivity. The average age of 47 years, however, presents threat concerns for the long-term sustainability of the cocoa industry.

The results also revealed that the average farm household was made up of about 5 household members who could contribute one way or the other to the farm activity depending on their economic strength and working-age qualification. It further suggests that on average all other things being equal, the household labour capacity of the farm household stands at 5. It was further realised that most of the farmers (79.31%) had received some level of formal education with the average years spent in school standing around 9 years. The above results on education stand to reason that there is an acceptable level of literacy among cocoa farmers. This, therefore, implies that the probability of the average farmer's ability to understand and appreciate technical information passed to them is quite substantial. Access to agricultural extension services is considered an important institutional variable that acts as a catalyst for change. The farmers interviewed affirmed that they had access to extension services with the frequency of extension contact ranging between 5 to 13 times within the production season with an average frequency of visit of about 7. It can thus be inferred that the average farmer had a considerable amount of extension contact. Hence, the ability to effect appropriate and timely measures to combat any identified production challenges. It can further be adduced that the average farmer receiving not less than 5 extension contacts, stands the chance of receiving the needed training and knowledge and technology transfer, with an added advantage to effectively carry out production activity.

Farming experience was considered an important variable in this study as it contributes to farmers' ability to sufficiently assert the occurrence of climate change and variability within their environment. The findings indicate that the farming experiences of farmers interviewed ranged from 10 years to 60 years with a mean of 18 years. The mean of 18 years suggests that the average farmer has enough experience to adequately appreciate whether there has been a significant change and/or variability in climate. This is because climate change is said to have occurred when there has been a statistically significant variation in either the mean state of the climate or in its variability, persisting for an extended period [typically a decade or longer] (IPCC working group, 2014). With not less than 10 years of farming experience, and per the minimum years (10 years) required for us to claim that climate change has occurred, one could confidently say that farmers do have a proper conceptualisation of climate change and variability based on observation and experience over the years. Additionally, it can also be inferred that the average farmer has acquired enough experience that gives an added advantage in making timely and appropriate production activity and decision-making for higher productivity improvement.

From Table 3.9, about 52.1 percent of the farmers belong to a farmer-based organisation and this is very essential to knowledge sharing among farmers. Membership to a farmer-based organisation as an important social interaction indicator in line with this result indicates that the promotion and facilitation of technology transfer among farmers would be greatly enhanced. In every farm business, access to credit is very important to the liquidity status of the farm enterprise. Hence, the study sought to find out whether cocoa farmers have access to credit facilities to finance their farm activity. The results as indicated in Table 3.9 shows that about 54 percent do have access to credit and 46 percent do not have access to credit facility. By inference, it could be adduced that more than half of farmers could raise external funds to meet their operating expenses for better productivity growth, whiles the rest must rely on internally generated funds to operationalised their production objectives. Given the high risk and uncertainty associated with agricultural production, it has been largely advocated that farmers need to adopt livelihood diversification as an adaptation option to cushion that against potential shocks.

From the study, it was realised that about 51 percent of the farmers interviewed do engage in extra economic activity aside from cocoa farming, whiles the remaining 49 percent solely depends on farming as the main economic activity. With this, one could conclude that in the advent of shock in agricultural productivity and income, about 51 percent of the farmers have alternative means of cushioning themselves and that they would not be adversely affected, all other things being equal compared to their counterparts who solely depend on farming for survival. It is, therefore, important that coordinated effort is put in place by the government through its frontier agency, COCOBOD to get farmers to go into enterprise and livelihood diversification to increase their household income and ability to withstand potential shocks in productivity and income especially with the increasing trend of climate change and variability. Concerning capital, the computed annual depreciation value of the available capital assets was found be to GH¢ 507/ha. The results as portrayed in Table 3.9 also indicated that the average farm size was about 5 hectares and this is found to be consistent with the national average of 2 to 8 hectares as suggested by COCOBOD.

The results further reveal that the average farm output per hectare of land was found to be 874kg (approximately 16 bags). This output level was realised from the following input combination: 199kg/ha of fertiliser, 2 litres/ha of pesticides and 82 man-days/ha of labour. The output level as realised from this study is found to be above the national average of about 350kg/ha to 400kg/ha. This result can largely be attributed to the use of the recommended fertiliser rate of not less than 150kg/ha by the farmers.

3.18 Chapter Summary

This chapter discussed the methodological procedures that were employed in this study. It discussed the research design, study area, population, sample and sampling procedure, and data collection, data processing and analysis procedures. Summary statistics of farmer-specific characteristics of cocoa were also discussed.

CHAPTER FOUR

FARMERS PERCEIVED CLIMATE VARIABILITY AND CLIMATE SMART ADAPTATION CHOICES

4.1 Introduction

The chapter presents results and discussion concerning the first research objective. That is, farmers perceived climate variability and climate smart adaptation choices. The results discussed here included analysis of cocoa farmers' perception of climate change and variability, analysis of climate smart adaptation among cocoa farmers, and the analysis of the drivers of cocoa farmers climate smart adaptation choices.

4.2 Analysis of Cocoa Farmers' Perception of Climate Change and Variability

The perception of climate change and variability based on the experiential knowledge of farmers within the local context has contributed to advancing the understanding of climate change and its impact or adverse consequence on agriculture. Again, cocoa farmers' perception of climate change and variability is relevant for climate smart adaptation responses. For instance, Denkyirah *et al.* (2017) opined that a better understanding of climate change perception helps identify knowledge gaps of cocoa farmers on climate change and provides the platform for equipping them with the requisite knowledge and skills on climate change and the adaptation responses that would help improve cocoa productivity. Accordingly, farmers were assessed on whether they have observed any significant variability in rainfall and temperature over the years. Again, the perceived impact and future threat of climate change on productivity were evaluated.

Following the quartile distribution principle, a quarterisation of farmers perception index score was done to group farmers into four categories with the descriptions (low perception index: 0 -0.24; moderately low perception index: 0.25 -0.49; moderately high perception index: 0.50 – 0.74; and high perception index: 0.75 – 1.00). The results of the analysis are presented in Table 4.1.

Table 4.1: Distribution of Farmers Based on their Perception of Climate Change and Variability

Variable	**Perception index classification**				**Mean index**
	Low (0 -0.24)	**Moderately Low (0.25 -0.49)**	**Moderately High (0.50-0.74)**	**High (0.75-1.00)**	
Perceived rainfall variability	54 (8%)	132 (18%)	345 (48%)	189 (26%)	0.60
Perceived temperature variability	42 (6%)	106 (15%)	276 (38%)	296 (41%)	0.62
Perceived impact or adverse consequences of climate change on productivity	53 (7%)	133 (18%)	346 (48%)	188 (27%)	0.60
Perceived future threat of climate change on productivity	62 (9%)	156 (22%)	404 (56%)	98 (13%)	0.54

Source: Field Survey, Inkoom (2019) n=720

As shown in Table 4.1, the percentage distribution indicates that the majority (i.e., about 74 percent) of the farmers perceived a long-term moderately high to high variability in rainfall. This was attributed to the observed unpredictable pattern of rainfalls over the years, the onset of rains, the number of rainy days, the spread of the rainy days and the persistent decrease in rainfall as observed by the farmers. In general, the average perception index in rainfall variability was found to be 0.60. This indicates that the perceived variability in rainfall was moderate to high. This by implication suggests that indeed based on the experiential evaluation and cognitive assessments of farmers, there has been significant variability in rainfall over the years. This indeed confirms observed historical climate data as reported by Dadzie (2016).

Furthermore, the percentage distribution of farmers according to temperature variability perception indicates that the majority (i.e., about 79 percent) of the farmers perceived a long-term moderately high to high variability in temperature. The estimated mean perception index for temperature variability was found to be 0.62 and this suggests an affirmation of moderate to high temperature variability from the perceptive of farmers. This was reflected in the persistent increase in temperature. Specifically, farmers indicated that they had observed a persistent increase in the hotness of the temperature. The observed mean perception index for temperature by implication suggests that indeed based on the experiential evaluation and cognitive assessments of farmers, there has been significant variability in temperature over the years which confirm objective historical climate data as reported by Dadzie (2016). Now the import of the results on the perceived variability in rainfall and temperature as noted from the study is that the average farmer having perceived significant change in the climate is more likely to adopt climate smart adaptation strategies to reduce the impact on their production. The observed results on perceived variability in rainfall and temperature by cocoa farmers are consistent with the findings of other studies (Denkyirah *et al.*, 2017; Yamba, Appiah, & Siaw, 2019; Buxton, Lamptey, & Nyarko, 2018).

The results on the perceived impact (adverse consequence) and future threat of climate change on cocoa production as presented in Table 4.1 indicate that the average perception index for perceived impact and future threat of climate change on productivity was 0.57 and 0.54 respectively. These results suggest a moderate degree of impact and threat. Again, the percentage distribution reveals that most of the farmers (i.e., about 75 percent) perceived a moderately high to high adverse consequence of climate change on cocoa productivity. This by inference means that cocoa farmers have observed significant adverse effects of climate change on their productivity. This was coupled with an observed threat for the future, given the persistent increasing trends of climate change. It was noted that about 69 percent of the farmers perceived that the degree of climate change threat was moderately high to high. The generally observed moderate level of impact and threat of climate change can be attributed to the similar climatic features that characterise the cocoa production regions. For instance, the bimodal rainfall patterns and forest nature of the vegetation across these regions provide some level of natural cushioning for farmers against climate change effects. However, with the expansionist production systems and the likelihood of experiencing a long dry spell and other extreme weather events, there is a need for climate smart adaptation to make farmers more resilient in the near future.

4.3 Analyses of Climate Smart Adaptation Choices among Cocoa Farmers

Adaptation to climate change necessitates that, farmers must first acknowledge that the climate has changed, then identify appropriate adaptations options and respond to them appropriately. It is argued here that, it is only when farmers perceive current and future climate change as a reality, will they choose to adopt. Thus, farmers' perception of climate change and variability was firstly looked at. After exploring farmers’ perception of climate change and variability, the study went further to identify the adaptation options available to cocoa farmers and the adaptation responses currently being implemented at the farm levels. This section, therefore, presents results and discussions associated with the adaptation choices of cocoa farmers. Farmers were presented with eleven recommended climate smart adaptation strategies to indicate their awareness and use of it. Also, farmers were asked to indicate their perceived effectiveness of CSA choices as well as their risk perception towards investing in them. The results are presented in Table 4.2.

Table 4.2: Distribution of Climate Smart Adaptation (CSA) Choices among Cocoa Farmers

Climate smart adaptation choices	**Currently aware of CSA option**		**Currently, use the CSA option**	
	Freq.	%	Freq.	%
Use of improved crop varieties	637	88.5	582	80.8
Optimum use of fertiliser	665	92.4	633	87.9
Optimum use of pesticides	652	90.6	614	85.3
Practice of shade tree management	606	84.2	574	79.7
Practice of changing planting date	445	61.8	382	53.1
Practice of crop diversification system	606	84.2	570	79.2
Practice of non-crop diversification system	565	78.5	495	68.8
Practice of off-farm diversification system	382	53.1	338	46.94
Subscription to crop insurance	232	32.2	-	-
Practice of irrigation system	462	65.0	-	-
Practice of hand pollination system	457	63.5	-	-
Percentage rate of awareness of CSA		72.1%		
Percentage rate of usage of CSA		52.4%		
Summary based on Categorisation	**Below 5**		**5 to 8**	**Above 8**
Total count of CSA measures currently being practised by farmers	140 (19 %)		580 (81%)	0
Mean number of CSA measures currently adopted by farmers				***6***

Source: Field Survey, Inkoom (2019) n = 720

The results as presented in Table 4.2 indicate that farmers on average were aware that all the eleven CSA strategies presented to them are potential adaptation responses or choices to climate change. In all, except for subscription to crop insurance, all the CSA options presented to farmers had an awareness rate of more than 50 percent, with the overall awareness rate being 72.1 percent.

This indicates that cocoa farmers to a large extent acknowledge that the eleven recommended CSA options are indeed adaptation responses that can make them resilient to the adverse consequence of climate change. The result further shows that eight out of the eleven recommended CSA strategies were currently being used by farmers. Further probing shows that most of the farmers (81 percent) are currently using 5 to 8 CSA options, and the rest 19 percent using less than 5 CSA options. Farmers were currently not using three of the eleven recommended CSA options; that is, subscription to crop insurance, the practice of irrigation system and the practice of hand pollination system. On average, it was noted that farmers have adapted 6 CSA strategies, which suggests a satisfactory result. However, the overall adoption rate of CSA as indicated in Table 4.2 was about 52 percent. This by extension suggests that, the adoption penetration is just on average and that more needs to be done by all key stakeholders, especially COCOBOD to promote a higher adoption rate of CSA strategies to increase farmers' resilience and adaptive capacity to climate change effects.

Further, farmers' risk perception and perceived effectiveness of CSA technologies was assessed. Following the quartile distribution principles, farmers were grouped into four categories based on the quarterisation of the risk perception index and perceived CSA effectiveness index. The description of the quarterisation of the perception index was as follows: low perception index (0 - 0.24), moderately low perception index (0.25 - 0.49), moderately high perception index (0.50 – 0.74), and high perception index (0.75 – 1.00). The results of the distribution analysis are presented in Figure 4.1.

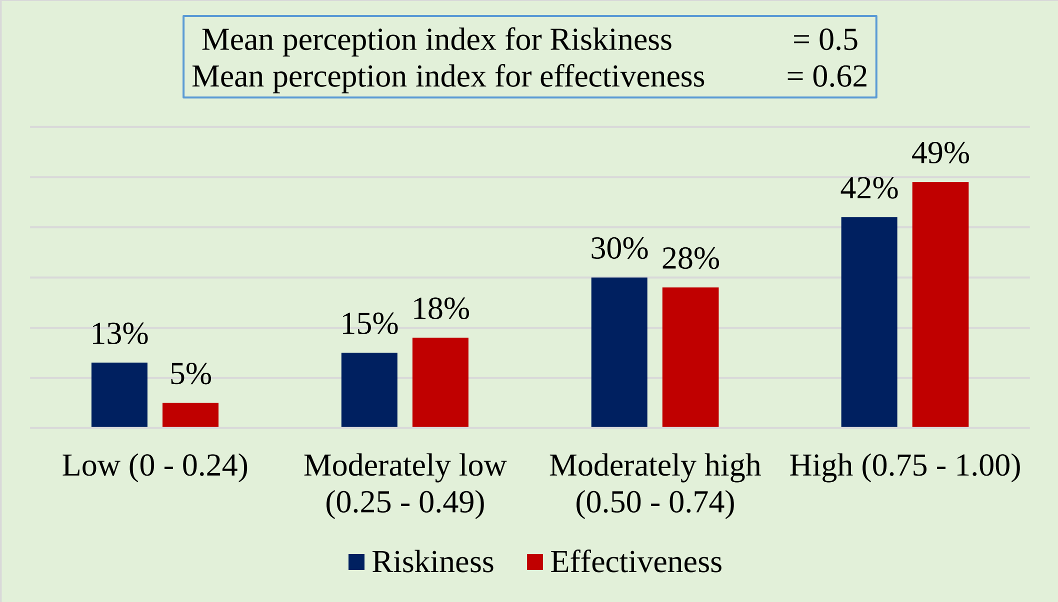


Figure 4.1:Distribution of Farmers Based on Risk Perception towards Investing in CSA and Perceived Effectiveness of the CSA Strategies

Source: Field Survey, Inkoom (2019) n = 720

The risk perception index was computed on a continuous scale of 0 to 1, indicating the degree of riskiness as we move from 0 to 1. From the result, the mean risk perception index of 0.57 was observed with about 72 percent of farmers falling within the risk perception index above 0.50. This, therefore, suggests a moderately high to high-risk attitude towards investment in CSA technologies among cocoa farmers. Given that risk perception has implications for adoption decision choices, the observed degree of riskiness as perceived by farmers can negatively impact the adoption penetration of CSA measures among cocoa farmers. This is because, when farmers are in a state of fear and uncertainty about the success of any CSA measures, it invariably tends to affect their willingness and promptness to take the necessary action as required. One possible reason that can be adduced to the observed risk perception degree among farmers could be attributed to the appropriateness and adequacy of CSA education and training to farmers and the potential benefits of CSA to cocoa production and livelihood security. This, therefore, calls for increased education and training effort from stakeholders, especially COCOBOD to farmers. Furthermore, the study observed that the mean perception index concerning the effectiveness of CSA was about 0.62, and that about 77 percent of farmers interviewed had an effectiveness perception index of 0.50 and above. This suggests that farmers were of the view that the effectiveness of the strategies in building their resilience to climate change was moderately high to high. Hence, it can be said the CSA strategies being practised by farmers are yielding dividends.

4.4 Effect of Climate Variability Perception on Cocoa Farmers Climate Smart Adaptation Choices

In the face of the increasing vulnerability to climate change effect, adaptation responses have received extensive attention in climate change debate. It is assumed that for higher resilience to climate change effect, it is prudent for farmers to adopt a mix of climate smart adaptation strategies, which presents a choice situation. In the economics of choice, farmers make adaptation decisions with the objective of utility maximisation (e.g., profit maximisation). This means that farmers may choose to adopt or not adopt a CSA strategy depending on the anticipated utility to be derived. In this case, choice models are appropriate for analysing the farmers' decision choices on climate smart adaptation. It is again premised that the decision to adapt to climate change is preconditioned on the acknowledge about the reality of climate change occurrence. Accordingly, the first research hypothesis of the study sought to empirical test the effects of climate variability perception on the adaptation choice decisions of farmers, by employing a multivariate probit model. The multivariate probit result is presented in Tables 4.3 and 4.4. Table 4.3 focuses on the test of the complementary relationship between the dependent variables and Table 4.4 presents a measure of the probability that each explanatory variable in the model explains the dependent variables.

To validate the first research hypothesis, two climate variability indicators (i.e., rainfall and temperature variability) was introduced into the multivariate probit model to test the influence of farmers perception about them on their climate smart adaptation choice. The significant rho value as presented in Table 4.3 revealed that the multivariate probit results adequately test the effect of climate variability perception on climate smart adaptation choices. This was further confirmed from the highly significant coefficient estimate associated with perceived rainfall variability and temperature variability as indicative in Table 4.4. From the model results, it was observed that both perceived rainfall variability and perceived temperature variability had a positive and significant impact on farmers climate smart adaptation choices. Accordingly, the study failed to accept the null hypothesis that "*Climate variability perception does not positively and significantly influence climate smart adaptation choices among farmers*" in favour of the alternative hypothesis that "*Climate variability perception positively and significantly influence climate smart adaptation choices among farmers*". Having ascertained the first research hypothesis, I now move on to discuss the implication of the observed results from the multivariate probit model as presented in Tables 4.3 and 4.4.

Assessing the Model Fitness of The Multivariate Probit and Complementary Relationship between the CSA Technologies

The multivariate probit model as a generalization of the ordinary probit model permits the estimation of several correlated binary outcomes jointly. For the model result to be accepted as unbiased and efficient, the rho estimates and chi-square value is used to judge whether the multivariate probit best fits the dataset than the ordinary probit model. For the model to be efficient and unbiased, rho which tests the assumption of a multivariate correlation between the multivariate binary outcome variables must be significantly different from zero. The log-likelihood ratio test result as presented in Table 4.3 shows that rho is significantly different from zero. This confirms the superiority of the multivariate probit model in giving robust and efficient results that best fits the dataset compared to the normal probit model.

Table 4.3: Multivariate Probit Results of Rho testing Relationship between CSA options

Variable Interaction	Coefficient	Std. Error	T value
CSA1*CSA2	0. 2422**	0. 0979	2.470
CSA1*CSA3	0. 0580	0.0941	0.620
CSA1*CSA4	0.3251***	0.0911	3.570
CSA1*CSA5	0. 1233	0.0864	1.430
CSA1*CSA6	0. 1137	0.0766	1.480
CSA1*CSA7	-0. 0783	0.0751	-1.040
CSA1*CSA8	0.1357*	0.0734	1.860
CSA2*CSA3	0.6012***	0.1049	5.730
CSA2*CSA4	0.0612*	0.0345	1.774
CSA2*CSA5	-0.0223	0.0969	-0.230
CSA2*CSA6	0.1166	0.0790	1.480
CSA2*CSA7	0.0672	0.0784	0.860
CSA2*CSA8	0.1908**	0.0765	2.490
CSA3*CSA4	0.0371	0.0912	0.410
CSA3*CSA5	0.1777*	0.0965	1.840
CSA3*CSA6	0.0035	0.0812	0.040
CSA3*CSA7	-0.0391	0.0789	-0.500
CSA3*CSA8	0.1570**	0.0774	2.030
CSA4*CSA5	0.3744***	0.0911	4.110
CSA4*CSA6	-0.0813	0.0778	-1.040
CSA4*CSA7	0.0683**	0.0289	2.363
CSA4*CSA8	0.0386**	0.0164	2.354
CSA5*CSA6	0.1989**	0.0771	2.580
CSA5*CSA7	0.0915	0.0753	1.220
CSA5*CSA8	0.0039	0.0741	0.050
CSA6*CSA7	0.3615***	0.0632	5.720
CSA6*CSA8	0.2931***	0.0662	4.430
CSA7*CSA8	0.2097***	0.0656	3.200
Significance codes: ‘***’ 0.01 ‘**’ 0.05 ‘*’ 0.1			
Log-likelihood ratio test of the relationship between dependent variables			
	LogLike	DF	Chi-square / P-value
rho12 = rho13,…, = rho78 = 0:	-1919.2		
rho12 = rho13,…, = rho78 ≠ 0:	-2719.1	-18	1599.8 / 2.2^{e-16} ****

Source: Field Survey, Inkoom (2019)

Again, the test result showed that the estimated chi-square value was high, suggesting an unbiased and efficient model result. In applying the multivariate probit model, it was assumed that the CSA options play complementary roles to each other. Thus, a mixture of them provides much better resilience to farmers. Accordingly, it became necessary to test whether there is a significant relationship between the eight CSA options as the dependent variables. This attests to the appropriateness of the choice of the multivariate probit model in analysing the determinants of the adaptation choices among farmers. The likelihood test result as presented in Table 4.3 again confirms that there is a significant complementary relationship between the CSA options. Consequently, by using a combination of the CSA options, an individual farmer will be better placed to adequately respond to climate change effects.

The dependent variable represents eight CSA strategies that are currently being used by farmers as a response mechanism to climate change and variability. This includes the use of improved crop varieties (CSA1), optimal fertiliser application (CSA2), optimal pesticide application (CSA3), changing of planting dates (CSA4), shade tree management (CSA5), crop diversification (CSA6), non-crop diversification (CSA7) and off-farm diversification (CSA8). The model test results show that there exists a joint decision process concerning the use of CSA practices given their complementary role. This result affirms the assertion that there is a joint decision process by farmers when it comes to farmers climate smart adaptation technologies adoption, which is aimed at maximising the potential utility benefit of adaptation (Issahaku & Abdulai, 2019; Denkyirah *et al*., 2017; FAO, 2013). For instance, the result suggests with an efficient combination of improved crop variety, optimal fertiliser application, changing planting date and off-farm diversification system as adaptation responses, there is the likelihood for farmers to significantly increase their resilience to climate change effect. This affirms the observation made by Denkyirah *et al*. (2017) where cocoa farmers adopted a mixture of CSA technologies as means of increasing their resilience to climate change effect. Again, it was noted that with an efficient combination of optimal fertiliser application, optimal pesticides application, changing plant date and off-farm diversification as adaptation responses, there is the likelihood for farmers to significantly increase their resilience to climate change effect. Furthermore, with an efficient combination of optimal pesticide application, shade tree management, and off-farm diversification as adaptation responses, there is the likelihood for farmers to significantly increase their resilience to climate change effect. The joint adaptation responses as observed in this study affirms the empirical observation made by Asante *et al*. (2017), asserting that as means of building strong resilience to climate change, cocoa farmers resort to multiple adaptation strategies.

In addition, the study result further suggests that with an efficient combination of changing planting dates, shade tree management, non-crop diversification and off-farm diversification as adaptation responses, there is the likelihood for farmers to significantly increase resilience to climate change. Again, with an efficient combination of shade tree management and crop diversification as adaptation responses, there is the likelihood for farmers to significantly increase resilience to climate change effect. It was further observed that an efficient combination of crop diversification and non-crop diversification as potential adaptation responses increases farmers likelihood of significantly increasing their resilience to climate. Lastly, the results suggest that an efficient combination of non-crop diversification and off-farm diversification as adaptation responses presents farmers an opportunity to significantly increase their resilience to climate change effect. In summary, the result confirms that promoting and encouraging farmers to adopt more than one CSA option reduces the adverse effect of climate change on productivity and livelihood security. The general observation is that the empirical finding as observed from Table 4.3 support the argument that t the best approach to building better resilience to climate change among cocoa farmers is to encourage the adoption of a mixture of CSA strategies (Issahaku & Abdulai, 2019; Asante *et al.*, 2017; Denkyirah *et al*., 2017; Kongor *et al*., 2017; FAO, 2013).

Analysing the Drivers of Cocoa Farmers CSA Choices

From the model fitness and presence of complementary relationship test as presented in Table 4.3, it was realised that the use of the multivariate probit model was appropriate for analysing the determinants of cocoa farmers CSA choices. As such, the multivariate probit result showing the coefficient estimates of the determinants of CSA choices among farmers is deemed unbiased and efficient. Accordingly, the results showing the significant drivers of CSA choices among farmers are presented in Table 4.4. The results reveal that perceived rainfall variability was positively and significantly related to the probability of adopting CSA measures such as changing planting dates, shade tree management, non-crop diversification and off-farm diversification. The result as portrayed in Table 4.4 further revealed the perceived impact of climate change on productivity positively and significantly influences the likelihood of farmers adopting CSA measures such as the use of improved crop varieties, practices of crop diversification and non-crop diversification as appropriate adaptation responses to the adverse effect of climate change.

Table 4.4: Multivariate Probit Results for the Determinants of Farmers' CSA Choices

	Dependent variables: Climate Smart Adaptation Options							
Explanatory Variables	Improve variety	Optimal Fertiliser application	Optimal Pesticides application	Changing Plant Date	Shade Tree Management	Crop Diversification	Non-Crop diversification	Off-Farm Diversification
Constant	-2.36*** (0.61)	-1.82***(0.64)	-3.92*** (0.71)	-3.72*** (0.67)	-2.61***(0.65)	-1.11** (0.51)	-1.21** (0.49)	-2.78*** (0.50)
Perceived rainfall variability	0.021(0.29)	0.232(0.35)	0.051(0.322)	1.063***(0.32)	1.692***(0.32)	0.393(0.26)	0.419*(0.25)	1.499***(0.26)
Perceived temperature variability	0.094(0.33)	2.301***(0.36)	1.603***(0.37)	0.131(0.36)	0.769**(0.35)	0.113(0.27)	0.731**(0.26)	1.709***(0.28)
Perceived impact of climate change	1.731***(0.49)	0.084(0.55)	0.606(0.55)	0.837(0.54)	0.509(0.52)	0.479***(0.04)	0.685*(0.41)	0.034(0.43)
Perceived future threat of climate change	0.092**(0.04)	1.189**(0.56)	0.495(0.57)	0.795(0.52)	0.484(0.53)	0.690***(0.13)	0.058**(0.02)	0.159***(0.05)
Awareness of CSA options as adaptation responses	2.767*** (0.33)	2.272*** (0.35)	3.364*** (0.38)	4.660*** (0.40)	3.983*** (0.36)	1.946*** (0.29)	2.668*** (0.30)	3.443*** (0.32)
Risk perception towards investing in CSA	-0.457*(0.25)	-0.582**(0.25)	-0.926***(0.27)	-0.206(0.27)	-0.353(0.25)	-1.230***(0.20)	-0.628***(0.18)	0.672***(0.20)
Sex	-0.184 (0.13)	-0.008 (0.16)	0.120 (0.15)	-0.122 (0.15)	-0. 061 (0.14)	0.089 (0.11)	0.132 (0.11)	0.018 (0.11)
Age	-0.006 (0.01)	0.006 (0.01)	0.002 (0.01)	0.021** (0.01)	-0.002 (0.01)	0.030*** (0.01)	0.098*** (0.01)	0.007 (0.01)
Education	0.036** (0.13)	0.018* (0.01)	-0.023 (0.02)	-0. 003 (0.01)	008(0.01)	0.009 (0.01)	0. 026** (0.01)	0.024** (0.01)
FBO membership	0.150(0.14)	0.268* (0.15)	-0.294* (0.15)	0. 690*** (0.15)	0. 256*(0.14)	0.183* (0.11)	-0.524** (0.11)	-0.235*** (0.11)
Farming experience	-0.002 (0.01)	-0.003 (0.01)	0.011 (0.01)	0.013 (0.01)	0.003(0.01)	-0. 017 (0.02)	-0. 024***(0.01)	-0.011*** (0.02)
Frequency of extension contacts	0.074** (0.03)	0.050 (0.03)	0.229*** (0.04)	0.105** (0.04)	0.124***(0.03)	0. 252** (0.13)	-0.005 (0.02)	-0.080 (0.13)
Access to credit	0.698*** (0.15)	0.237* (0.13)	0.288 (0.17)	0.134 (0.16)	0.129(0.16)	-0.093 (0.19)	0.452*** (0.13)	2.776*** (0.50)

NOTE: Digits in bracket represent the standard errors and those without bracket represents the coefficient estimates respectively

Significance codes: '' 0.01 '**' 0.05 '*' 0.1***

Source: Field Survey, Inkoom (2019

Equally, it was noted that the perceived future threat that climate change presents was positively and significantly related to the likelihood of farmers adopting CSA technologies such as optimal fertiliser application, use of improved crop varieties, crop diversification, non-crop diversification and off-farm diversification as appropriate adaptation responses to climate change. Furthermore, it was observed that CSA awareness positively and significantly influences the likelihood of farmers adopting all the eight CSA options as climate smart responses to climate change. This implies that creating a higher awareness among farmers on the potential benefits of adapting to climate will strongly impact their adaptation decision-making process with respect to any CSA technology that would be introduced to them.

In addition, farmers risk perception towards investing in CSA strategies negatively and significantly influences the likelihood of adopting CSA strategies such as optimal fertiliser application, optimal pesticides application, changing planting date, crop-diversification, non-crop diversification, and off-farm diversification. The import of this finding is that higher risk perception among farmers reduces the likelihood of farmers adapting to climate change. This could be attributed to perceived uncertainties associated with the potential benefit of agricultural technologies. The observed findings on risk perception and impact of climate change affirm the assertion that risk attitude and perceived impact of climate change have a significant influence on the adaptation behaviour among individuals (Khatri-Chhetr *et al*., 2017; Li *et al*., 2017; Barnes *et al*., 2013). In summary, the observed relationship between climate change indicators and farmers CSA choices is revealing and does attest to the potentials associated with each of the strategies. For instance, the adoption of improved crop varieties could be attributed to the high yielding potential, pest, and disease resistance and as well as drought resistance traits associated with improved crop varieties. Again, the optimal use of fertiliser and pesticides provides optimal yield security to farmers. Diversification strategies (i.e., crop diversification, non-crop diversification and off-farm diversification) provides appropriate livelihood security to farmers in terms of income and food security. Also, practices of changing planting dates and shade tree management help minimise uncertainties due to climate variability.

Concerning the impact of socioeconomic variables, age was found to influence the likelihood of farmers practising changing planting dates positively and significantly, crop diversification non-crop diversification as an appropriate adaptation response to climate change. This suggests that as farmers advance in years, there is the likelihood to diversify cocoa enterprises to include other crop and animal enterprises such as the rearing of small ruminants and poultry to complement household food availability and income. In addition, it was noted that the education level of farmers had positive and significant influences on the likelihood of farmers choosing to adopt improved crop varieties, optimal fertiliser application, and non-crop and off-farm economic diversifications as adaptation responses to climate change. This implies that farmers with higher education are more likely to adopt a variety of CSA options as a coping strategy to climate change effect. The observed influence of age and education on climate smart adaptation choices in the study is consistent with other empirical findings on drivers of climate smart adaptation choices among farmers (Issahaku & Abdulai, 2019; Akrofi-Atitianti *et al*., 2018; Denkyirah *et al*., 2017).

The result as presented in Table 4.4 indicates that membership to FBO positively and significantly influences the decision to practice optimal fertiliser application, changing of plant dates, crop diversification and shade tree management as appropriate adaptation responses to climate change. This means that members of FBO were more likely to adapt to climate change using varied adaptation options. This could be attributed to the benefits of social interaction such as trust and experiential learning and sharing of ideas. It was further noted that FBO membership negatively and significantly influences the likelihood of farmers choosing to adopt optimal pesticides, non-crop diversification, and off-farm diversification as adaptation responses to climate change. This suggests that non-members of FBO were likely to adapt to climate change. This could be attributed to the possibility of the non-FBO members getting access to better information on the optimal fertiliser application, non-crop and off-farm diversification giving them an added advantage over their counterparts. Furthermore, it observed that years of farming experience negatively and significantly influence the decision to diversify via non-crop diversification and off-farm diversification. Thus, it can be said that farmers with more years are less likely to adapt to climate change through non-crop diversification and off-farm diversification. The observed significant impact of membership to FBO and Farming experience on climate smart adaptation among farmers support the asserted influence of these variables on climate smart adaptation choices among farmers as reported by other study findings (Acquah *et al*., 2017; Denkyirah *et al*., 2017; Ehiakpor *et al*., 2016).

As expected, frequency of extension contact was found to be positively and significantly related to the likelihood of farmers choosing to use improved crop varieties, optimal pesticide application, changing of planting dates, shade tree management, and crop diversification as appropriate adaptation responses to climate change. This observation could be attributed to the current COCOBOD programme on farmer-field schools and cocoa rehabilitation programmes where farmers are educated and given incentives to diversify and adopt efficient shade tree management and pesticides and disease control measures. Finally, access to credit positively and significantly influences the likelihood of farmers deciding to adopt improved crop varieties, optimal fertiliser application, non-crop diversification and off-farm diversification as effective adaptation responses to climate change. This suggests that increasing farmers' access to credits will positively enhance their ability to adapt appropriately to climate change. The study results as observed in Table 4.4 further advance empirical supports to other study findings on the impact of extension access and credit access on the adaptation behaviour among farmers (Issahaku & Abdulai, 2019; Denkyirah *et al*., 2017; Acquah *et al*., 2017).

4.5 Chapter Summary

The chapter presented the discussed results on farmers perceived climate variability and climate smart adaptation choices. The results showed that perceived climate variability significantly explains climate smart adaptation choices among farmers. The next chapter discusses results on farmers perceived extension service quality and willingness to pay for climate smart cocoa extension service delivery.

CHAPTER FIVE

FARMERS PERCEIVED EXTENSION SERVICE QUALITY AND WILLINGNESS TO PAY FOR CLIMATE SMART COCOA EXTENSION SERVICE DELIVERY

5.1 Introduction

The second research objective was to assess how extension service quality influences willingness to pay for climate smart cocoa extension service among cocoa farmers. The results presented here covers farmers perceived extension service quality, farmers' preference and willingness to pay for climate smart cocoa extension service and the effect of extension service quality on farmers' willingness to pay behaviour.

5.2 Farmers' Perceived Extension Service Quality

This study estimated the agricultural extension service quality in Ghana by focusing on cocoa farmers' perceptions of the service quality received. As argued by service quality experts (Parasuraman *et al*., 1991; Cronin *et al*., 1994; Adil *et al*., 2013; Park, 2016; Ali *et al*., 2017) the decision of consumers to continue utilising a service depends on the utility derived from the use of that service; which is a function of the perceived quality of the service delivered with respect to tangibility, reliability, responsiveness, assurance, and empathy. Service quality is an indication of service performance as experienced by consumers. As posited earlier, cocoa farmers like any other service users are much concerned with optimal delivery of service provision. In that, the utility derived from the use of the service is the function of the quality of the service. Hence, their evaluation of service quality is a function of their affective and cognitive judgement on actual service performance as experienced. Farmers were asked to assign a performance score to the quality of cocoa extension service received on a continuous scale of 1 (definitely very low) to 10 (definitely very high).

To place the argument within the context of the optimal performance frontier, Equation 3.4 was followed to generate a service quality index, depicting the extent of service quality. The index is bounded between 0 (definitely very low) to 1(definitely very high), where a movement from 0 to 1 indicates an increasing degree of service quality and vice versa. The mean scores, frequencies, and percentage distribution of farmers' perceptions of the service quality dimension are indicated in Table 5.1. The findings reported here give the cognitive representation of the experiential knowledge and verdict of farmers on the kind of service received as well as the performance of the extension service providers. Based on the estimated service quality perception index, a quarterisation procedure following the quartile distribution principles was used to group the perception index into four categories. The description of the quarterisation of the perception index was as follows: low perception index (0 - 0.24), moderately low perception index (0.25 - 0.49), moderately high perception index (0.50 – 0.74), and high perception index (0.75 – 1.00).

The results of the distribution analysis are presented in Table 5.1. From Table 5.1, it can be observed that farmers are not satisfied with the overall service quality since the overall mean quality index is found to be 0.69, with a 0.31 deviation from the optimal service performance frontier. The mean quality index of 0.69 implies that the extent of service quality as perceived by the farmers is moderately high with performance standing around 69 percent.

Table 5.1: Estimates of Extension Service Quality and Service Quality Gap as Experienced by Cocoa Farmers

Service Quality Dimensions	Low 0 – 0.24	Moderately low 0.25–0.50	Moderately high 0.51-0.74	High 0.75-1.0	Mean	GAP
Tangibility	35 (4.9%)	105 (14.6%)	212 (29.4%)	368 (51.1%)	0.68	0.32
Reliability	44 (6.1%)	122 (15.9%)	241 (34.5%)	313 (43.5%)	0.67	0.33
Responsiveness	51 (7.1%)	127 (17.6%)	203 (28.2%)	339 (47.1%)	0.68	0.32
Assurance	36 (5%)	70 (10%)	173 (24%)	441 (61%)	0.74	0.26
Empathy	56 (8%)	94 (13%)	224 (31%)	346 (48%)	0.72	0.28
Total service quality	32 (4.4%)	90 (12.5%)	282 (39.2%)	316 (43.9%)	0.69	0.31

Source: Field Survey, Inkoom (2019) n = 720

By inference, the service performance of the cocoa extension service is about 69 percent. The 0.31 deviation from the performance frontier suggests a quality gap of about 31 percent. With this, it can be concluded that cocoa extension service providers need to work hard to address the shortfalls in their service delivery to farmers. The quality shortfall in extension service delivery as observed in this study confirms other study findings in which the was a general agreement among farmers that the quality of extension service received was belong the expected benchmark (Abdel-Ghany & Diab, 2015; Baudi *et al*., 2013; Rana *et al*., 2013; Abdel-Ghany & Abdel-Salam, 2012)

From the percentage distribution, it can be realised that about 83 percent of the farmers consider the quality of the service received to be moderately high to high, with only 17 percent indicating the service received was moderately low to low. This translates into the overall average perception of service quality of 0.69 which suggests a moderate quality of service. Looking at the overall quality index, we can say that, the utility farmers derive from the use of the extension service received is moderate and that if nothing is done to improve service performance it can consequently impact their willingness to continue patronising the service. This eventually might affect the efficiency of the use of the knowledge and technology obtained from the service delivery in their production activity to generate significant growth.

As indicated in Table 5.1, service tangibility was found to be moderately high with an index score of 0.68 and a 0.32 deviation from the optimal service performance frontier. This means farmers perceive the appropriateness of the physical, human, and technological resource capacities required to provide effective and efficient extension service to be moderate. The mean of 0.68 also implies there is a quality gap of about 32 percent. This requires that service providers must work hard and put the needed machinery and structures in place to address the 32 percent gap in the appropriate of both human and non-human resources needed to rendered quality service to farmers. The service quality shortfall with respect to the tangibility dimension of service quality as noted from the study result is consistent with the observation made by Rana *et al*. (2013) when it comes to the service performance of agricultural service providers. The mean quality index of 0.68 for the responsiveness dimension implies that from the perspectives of farmers', extension service providers showed a moderate level of willingness in providing rapid response to their concerns. This invariably suggests a moderate level of ability to provide prompt service to consumers. The score of 0.68 quality index of service responsiveness indicates a 0.31 deviation from the optimal performance frontier. It can thus, be inferred that the service quality gap with reference to responsiveness was about 32 percent and that the service providers need to work hard to make up for the shortfalls in their ability to render rapid response and prompt services to consumers. The quality shortfall with respect to the responsiveness dimension of service quality as noted from the study result is consistent with the observation made by Abdel-Ghany and Abdel-Salam (2012) when it comes to service performance of agricultural service providers.

The mean quality index of 0.67 for service reliability also suggests that cocoa farmers perceived that the extension service providers have a moderate ability to appropriately provide accurate and dependable services as promised. Also, as indicated in Table 5.1, service reliability recorded about 0.33 deviation from the optimal performance frontier, suggesting a service quality gap of about 33 percent. This suggests a shortfall in the reliability of the service delivered. As such, the extension service providers need to put in the appropriate measures to enhance their ability to provide accurate and dependable service to farmers. The quality shortfall with respect to the reliability dimension of service quality as noted from the study result is consistent with the observation made by Abdel-Ghany and Diab (2015) when it comes to service performance of agricultural service providers. Table 5.1 further reveals that the quality index for service assurance was about 0.74 with 0.26 deviation from the optimal performance frontier. This mean perception index suggests a moderately high service quality. Further, the values indicate that, in the opinion of farmers, the knowledge and courtesy of extension service providers and their ability to convey trust and confidence was moderate. Hence, the service quality gap with respect to assurance is about 26 percent. The quality shortfall with respect to the responsiveness dimension of service quality as noted from the study result is consistent with the observation made by Abdel-Ghany and Abdel-Salam (2012) when it comes to service performance of agricultural service providers.

Additionally, as portrayed in Table 5.1, the mean quality index in reference to service empathy was found to be 0.72 with about 0.28 deviation from the performance frontier. The import of this estimated value is that from the perspective of farmers the ability of service providers to identify themselves with consumers' concerns, understand their problems and accurately fix it through specialized individual attention was moderate. It further implies that the quality gap for service empathy was about 28 percent and this indicates a significant shortfall in the service quality and performance so far as empathy is concerned. Additionally, the mean quality indexes for all the five dimensions of service quality being less than 1 suggests a general shortfall in the service performance by the extension service providers. Thus, the extension service providers must work hard to put the necessary structures and systems in place to address the shortfalls in the quality of the service rendered to ensure efficient utilisation by the consumers. From the observed results as presented in Table 5.1, it can conclusively be said the findings of the study advance empirical supports to the reported significant shortfalls in the quality of extension service delivered to farmers and as well as the performance of service providers (Abdel-Ghany & Abdel-Salam, 2012; Abdel-Ghany & Diab, 2015; Buadi *et al*., 2013; Rana *et al*., 2013; Lamontagne-Godwin, Williams, Bandara, & Appiah-Kubi, 2017).

5.3 Farmers' Preference for Climate Smart Cocoa Extension Service with Preference Heterogeneity

With the increasing adverse effect of climate change and variability on cocoa production, extension service as an institutional variable is critical in building cocoa farmers capacity to respond effectively and efficiently to climate change. This however would require the need to be climate smart. The study, therefore, recognizes the climate smart cocoa extension service (CSCES) as a powerful tool to reduce the effect of climate change and variability on cocoa productivity and increase the resilience and the adaptive capacity of cocoa farmers in Ghana. Accordingly, following a DCE approach, hypothetical choice cards were designed to collect stated preference data to investigate farmers' preference and willingness to pay for a climate smart cocoa extension service delivery. The stated preference data obtained from the experimental survey was then analysed using the mixed logit model following the simulated maximum likelihood approach. The simulated maximum likelihood estimates for the random parameter mixed logit model is reported in Table 5.2. The model was estimated using 1000 Halton draws to maximise the efficiency of the parameter estimates. In addition, the modelling assumed normal distribution for all the attributes. From the economic principle of the inverse demand function, farmers are assumed to have a homogeneous negative preference for price.

Accordingly, the price attribute of CSCES was assumed to be fixed while the rest of the attributes were assumed to be random with preference heterogeneity. The choice of the normal distribution was premised on the assumption that when it comes to improving extension service to be climate smart, it was logical to expect that at least some of the farmers would have a positive preference for the non-price attributes of the CSCES scheme (i.e., service accessibility, service content, service responsiveness, and service reliability). Additionally, the decision to specify the distribution of price attribute as constant was to avoid the likelihood of getting extreme negative or positive trade-off values, which might affect the estimation of the distribution of the willingness to pay estimates (Train, 2009, 2016; Hensher, Rose, & Greene, 2005).

Table 5.2: Maximum Likelihood Estimates of Mixed Logit Model of CSCES Choice with Preferences Heterogeneity

Variables		Coefficient	Std. Error	Z-value
Product Attributes:				
Alternative specific constant (ASC)		-3.8701 ***	0.2339	-16.5463
Price		- 0.1148 ***	0.0151	-7.6043
Service Accessibility		0. 3017 ***	0.0339	8.8867
Service Content		0.8714 ***	0.0562	15.5174
Service Responsiveness		0.8266 ***	0.0810	10.2003
Service Reliability		0.3594**	0.1339	2.6846
Standard deviation of mean of random parameters:				
Sd. Service Accessibility		0.3125***	0.0422	7.4100
Sd. Service Content		0.8896***	0.0600	14.8260
Sd. Service Responsiveness		1.2534***	0.0677	18.5191
Sd. Service Reliability		0.1640***	0.0129	12.6181
Heterogeneity in the mean of random parameters:				
Accessibility*sex		-0.0333**	0.0151	-2.2037
Accessibility*Age		0.0373**	0.0137	2.7172
Accessibility*Education		0.0315*	0.0172	1.8300
Accessibility*Farm income		0.0365*	0.0194	1.8798
Content*Sex		0.1951*	0.1004	1.9433
Content*Age		0.0921**	0.0327	2.8172
Content*Education		0.0695**	0.0284	2.4476
Content*Farm income		0.0185*	0.0098	1.8884
Responsiveness*Sex		0.0225**	0.0008	2.6422
Responsiveness*Age		0.0021**	0.0005	3.7017
Responsiveness*Education		0.0034***	0.0004	5.3232
Responsiveness*Farm income		0.0002**	0.0001	2.9095
Reliability*Sex		0.0811**	0.0375	2.1592
Reliability*Age		0.0900**	0.0286	3.1434
Reliability*Education		0.0522*	0.0306	1.7065
Reliability*Farm income		0.1056**	0.0294	3.5859
Model goodness-of-fitness: loglikelihood ratio test	AIC	LogLike.	Chi-square	p-value
	2971.634	-4904.6	1710.5	< 2.22^{e-16}

*Signif. codes: '***' 0.01 '**' 0.05 '*' 0.1*

Source: Field Survey, Inkoom (2019).

Now to validate whether the estimated mixed logit results as presented in Table 5.2 is efficient and robust as compared to the conditional logit model, a log-likelihood ratio test was performed. From the table, the goodness-of-fit test validates the suitability of the mixed logit to the dataset and its superiority in presenting a robust and efficient estimate. The significant Log-likelihood estimate as collaborated by the chi-square and p-value and the high AIC value, suggests that the mixed logit model assuming a preference heterogeneity perfectly best fits the stated preference data. Furthermore, the standard deviation associated with the mean of each random parameter coefficient reflects the variability that exists around the sample population. From the result, the standard deviation of each random parameter was found to be significant; indicating the presence of unobserved heterogeneity in the population. Moreover, the alternative specific constant was found to be negative and significant, suggesting that farmers benefit from choosing an alternative rather than opt-out. This implies that opting for a climate smart cocoa extension service delivery will provide better climate resilience benefits to cocoa farmers. The model fitness test suggests that the estimated model results are unbiased and efficient and thus the result can be accepted and discussed, making the necessary inferences.

The model results as presented in Table 5.2 show that all the estimated coefficients of the attributes are significant and have the expected sign. The price attribute was found to be negative and significant, suggesting that farmers utility decreases with price increases. In other words, farmers will have higher disutility or aversion for a climate smart cocoa extension service scheme that is very expensive. This observed negative preference for price by the farmers confirms other study findings where farmers were noted to exhibit a natural dislike for a higher price (Castellani *et al*., 2014; Vassalos & Lim, 2016; James *et al*., 2011). The result further shows that the service accessibility attribute is positive and significant, suggesting that farmers have higher utility for the in-person face-to-face accessibility mode compared with the virtual accessibility mode. This by implication means that farmers would prefer a face-to-face mode of delivery for the climate smart cocoa extension service. Again, the result shows that the coefficient of the service content attribute is positive and significant. This suggests that farmers have a higher utility for the advanced climate smart cocoa extension service attribute [ACSCES] compared to the traditional cocoa extension service attribute [TCES]. Thus, if farmers are offered the CSCES product, they would prefer service content that includes climate-smart adaptation packages such as shade tree management, enterprise diversification, insurance packages, irrigation package, pruning services, inputs delivery service, artificial insemination or hand-pollination service, weather information service and digital information service.

In addition, it was observed that the coefficient of the service responsiveness attribute is positive and significant. And this suggests that farmers have a higher utility for the flexible demand-based service delivery mode compared with the fixed schedule service delivery mode. By implication, farmers will prefer that the frequency of service contact for the CSCES focuses on the flexible demand-based service delivery option. Finally, the study results as portrayed in Table 5.2 shows that the coefficient of the service reliability attribute is positive and significant. By this, it can be deduced that farmers utility with respect to service accuracy and dependability increases as the degree of service reliability increases. Hence, an improvement in service reliability attribute from the 50 percent benchmark (an above-average service reliability attribute) would significantly increase the likelihood of farmers preference for the CSCES scheme.

To account for the source of heterogeneity as suggested by the significant standard deviation of the random attributes, selected socioeconomic variables were interacted with each random attribute within the mixed logit framework. The interaction process was repeated in a stepwise manner until the best socioeconomic predictors were obtained. From the results, it was noted that the socioeconomic variables that significantly explain the preference heterogeneity are sex, age, education, and farm income. The model results as portrayed in Table 5.2 show that sex interacted positively with all the attributes except the accessibility attribute. This suggests that male farmers have a strong preference for the advanced climate smart cocoa extension service content attribute, the flexible demand-based service delivery attribute, and an above-average service reliability attribute (i.e., service reliability above 50 percent threshold). Again, the result suggests that female farmers have a strong preference for the In-person face-to-face accessibility mode attribute.

The results further show that age interacted positively with all the four non-monetary attributes, suggesting that old farmers have a strong preference for the In-person face-to-face accessibility mode attribute, the advanced climate smart cocoa extension service content attribute, the flexible demand-based service delivery attribute, and an above-average service reliability attribute. More educated farmers were found to show a strong preference for the in-person face-to-face accessibility mode attribute, the advanced climate smart cocoa extension service content attribute, the flexible demand-based service delivery attribute, and an above-average service reliability attribute. Additionally, the result revealed an increase in farm income is likely to induce in farmers a strong preference for the in-person face-to-face accessibility mode attribute, the advanced climate smart cocoa extension service content attribute, the flexible demand-based service delivery attribute, and an above-average service reliability attribute.

Furthermore, to determine the share of the sample population that shows a positive preference for the non-monetary attributes of the CSCES, the cumulative probability of the standard normal deviate was computed. This was done by dividing the mean of each random parameter with their associated standard deviation. The output was then compared to the standard normal distribution table. For the service accessibility attribute, a cumulative probability value of 0.97 was obtained which when compared to the standard normal distribution table gave a share of 0.8339. This implies that about 83 percent of the farmers are estimated to prefer the in-person face-to-face accessibility mode of service delivery, with about 17 percent of them preferring the virtual accessibility mode of service delivery. Concerning the service content attribute, a cumulative probability value of 0.98 was obtained. This, when compared to the standard normal distribution table, gave a share of 0.8365, suggesting that about 84 percent of the farmers are estimated to prefer the advanced climate smart cocoa extension service with 16 percent of the farmers preferring the traditional cocoa extension service.

Again, for the service responsiveness attribute, the cumulative probability was estimated to be 0.66. This, when compared to the standard normal distribution table, revealed a value of 0.7454. This by extension implies that about 75 percent of the farmers are estimated to prefer the flexible demand-based service delivery option with 25 percent of them preferring the fixed schedule service delivery. Lastly, concerning the service reliability attribute, the cumulative probability value was estimated to be 2.2. Cross-checking this value with the standard normal distribution table gave a value of 0.9783. This stands to reason that about 98 percent of the farmers are estimated to prefer above-average service reliability in relation to service accuracy and dependability as far as service reliability is concerned.

5.4 Farmers' Willingness to Pay for Climate Smart Cocoa Extension Service (CSCES)

With the growing demand on government budget from competing sectors especially in the face of the increasing adverse consequence of climate change on agricultural productivity and farmers' livelihood; the need for providing efficient and effective climate smart cocoa extension service cannot be overemphasised. This, however, bring additional cost implication to the government. Worldwide, it has been argued that to help bridge the financing gap for efficient extension service delivery, there is the need for some fee-paying extension services delivery to complement the non-fee-paying one (Aydogdu, 2017). This, however, requires an empirical understanding of farmers' willingness to pay for fee-paying extension services. Accordingly, the current study estimated cocoa farmers marginal willingness to pay for a climate smart cocoa extension service using the willingness to pay space modelling approach. The results from the mixed logit model under the willingness to pay space framework are presented in Table 5.3.

The model results as presented in Table 5.3 indicate the monetary commitment farmers are willing and able to make towards any marginal improvement in the CSCES product attributes. In the estimation process, the minimum average base price used (i.e., service charge per month) was assumed to be GH¢ 10.0. This was based on literature search and expert opinion as well as pre-survey consultation with stakeholders and industry players.

Table 5.3: Willingness to Pay Space Estimates for the Marginal Improvement in the CSCES Product Attributes

Variables	Coefficient	Std. Error	Z-value
Service Accessibility	2.6272***	0.4137	6.3510
Service Content	7.5893***	1.0662	7.1179
Service Responsiveness	7.1987***	0.8913	8.0770
Service Reliability	3.1298**	1.3107	2.3878
*Significance codes: '***' 0.01 '**' 0.05 '*' 0.1*			

Source: Field Survey, Inkoom (2019).

From the results as presented in Table 5.3, it was observed that farmers are willing to pay GH¢ 2.60 for an improvement in the service accessibility attributes, giving that it will enhance the delivery of an efficient in-person face-to-face accessibility mode. This is because farmers showed a strong positive utility preference for the in-person face-to-face accessibility mode. Benchmarking this to the based price of GH¢ 10.00 suggests that farmers are will to pay about 26 percent more for an improvement in the service accessibility attribute of the CSCES scheme.

In addition, it was observed that cocoa farmers are willing to pay GH¢ 7.60 more for an improvement in the service content attribute, that guarantees the delivery of an efficient climate smart cocoa extension service content module. This is because farmers showed a strong utility preference for the advanced climate smart cocoa extension service content module. Now benchmarking the estimated WTP to the base price of GH¢ 10.00, reveals that cocoa farmers are willing to pay about 76 percent more for an improvement in the service content that focuses on climate smartness. It was further noted from the study results as portrayed in Table 5.3 that, cocoa farmers are willing to pay GH¢ 7.20 more for an improvement in the service responsiveness attributes which ensures the delivery of an efficient flexible demand-based service delivery module. This stems from the fact that farmers were noted to show a strong utility preference for the flexible demand-based service delivery mode of the service responsiveness attribute. Benchmarking the estimated WTP to the base price of GH¢ 10.00 reveals that farmers are willing to pay about 72 percent more for an improvement in the service responsiveness attribute of CSCES.

The study findings further revealed that farmers are willing to pay GH¢ 3.10 more for an improvement in the service reliability attribute, especially when this will lead to an increased degree of reliability with respect to accuracy and dependability. Referencing the estimated WTP to the base price of GH¢ 10 suggests that farmers are willing to pay about 31 percent more for an improvement in the service reliability attribute of CSCES. Cumulatively, the results as portrayed in Table 5.3 indicates that farmers are willing to commit an additional cedi amount for any marginal improvement in the non-monetary product attribute of the climate smart cocoa extension service scheme. However, it must be noted that per the results as presented in Table 5.3 farmers place more importance on the service content attribute and service responsiveness attribute than the service reliability and accessibility attributes. This gives useful information to service providers on how to package the CSCES scheme and present it to farmers. In summary, the observed findings as portrayed in Table 5.3 by implication suggests that on average farmers are willing to pay for any cost-sharing extension service that offers climate smart services which build their adaptive capacity as a response to climate change and enhance their resilience to climate change effect. This empirical evidence of farmers' willingness to pay for a fee-paying agricultural extension service delivery as observed in this study confirms other study findings (Uddin *et al*., 2016; Vassalos & Lim, 2016; James *et al*., 2011).

5.5 Effect of Extension Service Quality on Farmers Willingness to Pay for Climate Smart Cocoa Extension Service Scheme

Empirically, willingness to pay has been shown to vary with extension service quality (James *et al*., 2011). Consequently, as an enhancement to the policy implication of the estimated willingness to pay, the study sought to analyse how perceived extension service quality as an intrinsic factor predicts farmers' willingness to pay for the climate smart cocoa extension service scheme. Accordingly, the second research hypothesis sought to ascertain whether extension service quality positively and significant influences farmers willingness to pay behaviour. The modelling approach to validate this hypothesis was done under the mixed logit model estimation and the results presented in Table 5.4. The study result shows that perceived quality of extension service with respect to service quality dimensions (tangibility, reliability, responsiveness, assurance, and empathy) positively and significantly influences farmers' willingness to pay and this confirms findings from other studies (James *et al*., 2011).

Table 5.4: Determinants of Willingness to Pay for CSCES by Cocoa Farmers

Variable	Willingness to pay for the CSCES attributes:											
	Service Accessibility			Service Content			Service Reliability			Service Responsiveness		
	Coef.	SE	T-value	Coef.	SE	T-value	Coef.	SE	T-value	Coef.	SE	T-value
ESQTB	2.7052*	1.3960	1.9378	6.3801**	2.6140	2.4407	0.3008***	0.0709	4.2408	1.0443***	0.2905	3.5948
ESQRB	3.3723*	1.7886	1.8854	1.4991***	0.3780	3.9650	0.1767**	0.0792	2.2306	1.7237	3.6440	0.4730
ESQRP	0.4003	1.9124	0.2093	4.4679	3.5635	1.2538	0.0404	0.0825	0.4896	1.9498	3.7801	0.5158
ESQAS	4.1678***	1.5929	2.6165	7.5558**	3.0097	2.5105	0.0988	0.0651	1.5173	8.3789***	3.1530	2.6574
ESQEM	3.7714**	1.7516	2.1531	0.8764	3.1328	0.2798	0.0136	0.0728	0.1871	7.9212**	3.4605	2.2891
SEX	-1.4080	1.5604	-0.9023	-1.6042	3.0126	-0.5325	0.0610	0.0670	0.9106	-0.6673	3.0881	-0.2161
AGE	-3.7588***	1.3135	-2.8616	-1.2502	2.2950	-0.5448	-0.1863***	0.0576	-3.2335	-8.1301***	2.6898	-3.0226
EDUCATION	2.8215*	1.5873	1.7775	1.4080	2.9428	0.4785	0.0406	0.0667	0.6076	4.1079	3.0436	1.3497
CREDIT	1.7412	4.7679	0.3652	1.9370**	0.9710	1.9948	0.4676**	0.2143	2.1817	9.2255	9.7036	0.9507
INCOME	0.1118	0.2101	0.5321	0.3555	0.4019	0.8847	0.0253***	0.0096	2.6320	0.1059	0.4377	0.2420
RAIN_VP	0.6110	0.4580	1.3339	1.8139**	0.8868	2.0454	0.0408**	0.0201	2.0357	1.4329	0.9355	1.5317
TEMP_VP	1.7597***	0.5131	3.4295	1.6910*	0.8992	1.8806	0.7635***	0.2207	3.4585	5.9809	9.3598	0.6390
CCIMPACT	0.0062	0.0172	0.3626	0.0562*	0.0333	1.6871	0.0128*	0.0076	1.6693	0.0209	0.0351	0.5950

*Significance codes: '***' 0.01 '**' 0.05 '*' 0.1*

Source: Field Survey, Inkoom (2019).

In view of this, the study failed to accept the null hypothesis that "*Quality of extension service does not positively and significantly influence willingness to pay for climate smart cocoa extension service*" in favour of the alternative hypothesis that "*Quality of extension service positively and significantly influence willingness to pay for climate smart cocoa extension service*".

The result shows that an increase in the perceived quality of service tangibility (ESQTB) positively influences farmers' willingness to pay for the in-person face-to-face accessibility attribute, advance climate smart cocoa extension attribute, flexible demand-based service delivery attribute and an above-average service reliability attribute by a margin of 2.70, 6.30, 0.30 and 1.04 respectively. This by implication means that if extension service providers make effort to improve the appropriateness of both physical, human, and technological resource capacities required to provide effective and efficient service to farmers, it would consequently have a positive impact on farmers' willingness to pay for climate smart cocoa extension service. Furthermore, the results show that an increase in the perceived quality of service reliability (ESQRB) positively and significantly influences farmers' willingness to pay for the in-person face-to-face accessibility attribute, advance climate smart cocoa extension attribute, and an above-average service reliability attribute by a margin of 3.37, 1.49, and 0.17 respectively. Thus, it can be concluded that if extension service providers can engineer measures that can improve their ability to appropriately provide accurate and dependable services as promised to farmers, there will be a resultant positive impact on farmers' willingness to pay for climate smart cocoa extension service.

Additionally, the result indicates that an increase in the perceived quality of service assurance (ESQAS) positively influences farmers' willingness to pay for the in-person face-to-face accessibility attribute, advance climate smart cocoa extension attribute, and flexible demand-based service delivery attribute by a margin of 4.16, 7.55, and 8.37 respectively. This implies that if extension service providers can enhance their willingness and ability to provide rapid response to concerns of farmers and prompt service to farmers, there will be a consequential positive impact on farmers' willingness to pay for climate smart cocoa extension service. Again, it was noted that an increase in the perceived quality of service empathy (ESQEM) positively influences farmers' willingness to pay for the in-person face-to-face accessibility attribute and flexible demand-based service delivery attribute by a margin of 3.77 and 7.9 respectively. This suggests that an improvement in the ability of service providers to identify themselves with consumers' concerns, understand their problems and accurately fix them through specialized individual attention, there will be a resultant positive impact on farmers' willingness to pay for climate smart cocoa extension service.

From the empirical relationship observed between service quality dimensions and willingness to pay, it is now evident that increase access to extension service is key. However, if we are to achieve any positive results and simulate higher subscription to a fee-paying extension service scheme, neglecting the quality of service delivered will be detrimental to every effort made in this direction. From the observed significant relationship observed between extension service quality dimensions and willingness to pay, the current study concludes that there is indeed a significant relationship between perceived extension service quality and farmers' willingness to pay. Furthermore, it was noted age negatively and significantly influence willingness to pay. The result suggests that older farmers were less willing to pay for the in-person face-to-face accessibility attribute, an above-average service reliability attribute and the flexible demand-based service delivery attribute by a margin of 3.76, 0.19 and 8.37 respectively, which is not surprising because older people tend to be more sensitive to higher service charges for any of the product attributes.

In addition, it was observed that there is a positive relationship between educational level and willingness to pay. The result suggests that more educated farmers were more willing to pay for the in-person face-to-face accessibility attribute by a margin of 2.82. Access to credit facilities was found to positively and significantly influence farmers' willingness to pay. It observed that farmers who have access to credit facilities were more willing to pay for the in-person face-to-face accessibility attribute and an above-average service reliability attribute by a margin of 1.94 and 0.47 respectively. With this, creating a platform to enhance farmers' access to external credit facilities can stimulate a positive response in farmers' willingness to pay for any fee-paying extension service. It was realised from the result that farm income is a significant predictor of farmers' willingness to pay for climate smart cocoa extension service. Particularly, as shown in Table 5.4, farm income was found to have a positive influence on the willingness to pay for an above-average service reliability attribute by a margin of 0.03. This means that a unit increase in the average farm income of farmers will stimulate an increase in the willingness to pay for marginal improvement in the extension service reliability. The observed significant socioeconomic variables in this study corroborate findings from other studies on farmers' willingness to pay for extension service (James *et al*., 2011; Aydogdu, 2017).

Finally, the study also sought to assess the possible effect of farmers' perception of the occurrence of climate change and its observed impact on farmers' willingness to pay for a climate smart cocoa extension service. The results as portrayed in Table 5.4 reveal that perceived variability in rainfall (RAIN_VP) positively and significantly influence farmers' willingness to pay for advanced climate smart extension service attribute and an above-average service reliability attribute by a margin of 1.81 and 0.04 respectively. This suggests that an acknowledgement by farmers in the significant and persistent decrease rainfall, unreliable rainfall pattern and onset does have implications for their willingness to pay for any climate smart cocoa extension service. It was further observed that perceived variability in temperate (TEMP_VP) has a positive and significant relationship with farmers' willingness to pay for in-person face-to-face accessibility attribute, advance climate smart extension service content attribute, and an above-average service reliability attribute by a margin of 1.75, 1.69 and 0.76 respectively. This suggests that farmers' awareness of the occurrence of a significant and persistent increase in temperature potential affect their willingness to pay for an improvement in climate smart cocoa extension service delivery. Lastly, the result from Table 5.4 indicates that the perceived impact of climate change (CCIMPACT) on productivity positively and significantly influence farmers' willingness to pay for the advanced climate smart cocoa extension service content attribute and an above-average service reliability attribute by a margin of 0.05 and 0.01

respectively. It can thus be concluded that an accurate prediction and acknowledgement of farmers about the occurrence of climate change and its adverse consequence on farm productivity, is an important consideration to the willingness to pay for a climate smart cocoa extension service as a response to building resilience and adaptive capacity to climate change effect.

5.6 Chapter Summary

The chapter presented the discussed results on farmers' perceived extension service quality and their willingness to pay for a climate smart cocoa extension service delivery. The results revealed that, on average, farmers perceived the quality of service received to be moderate, and that their perceived quality of extension service significantly explains their willingness to pay for a climate smart cocoa extension service delivery. Again, perceived climate variability was found to significantly explain farmers' willingness to pay for climate smart cocoa extension service. The next chapter discusses results on the characterisation of farmers based on their efficiency of production and household food security situation.

CHAPTER SIX

CHARACTERISING COCOA FARMERS BASED ON EFFICIENCY OF PRODUCTION AND FOOD SECURITY ESTIMATES

6.1 Introduction

The chapter presents results and discussion on research objectives three and four (i.e., efficiency of production and food security estimates). The study employed the Cobb-Douglas stochastic production and cost frontier models to estimate technical efficiency, allocative efficiency, and economic efficiency levels among cocoa farmers. A multidimensional food security framework was used to estimate and characterise the household food security of cocoa farming households in Ghana. The results are thus presented in the subsequent sections.

6.2 Estimates of the Stochastic Production and Cost Frontier Models

The third research objective sought to estimate the efficiency of production among cocoa farmers. To arrive at this, the Cobb-Douglas Stochastic Production and Cost Frontier Models were employed. Table 6.1 presents the result for the maximum likelihood estimates for the Cobb-Douglas stochastic production and cost frontier models. The appropriateness and superiority of the Cobb-Douglas function in giving robust and efficient results for the dataset was tested against the no-inefficiency frontier (i.e., OLS model). The log-likelihood ratio test revealed that the Cobb-Douglas functional specification appropriately and accurately fits the data and thus produces efficient estimates for the stochastic production and cost frontier models. Again, the result of the log-likelihood test suggests that the error component frontier (i.e., SFA model) better fits the data than the no inefficiency frontier (i.e., OLS model).

Table 6.1: Maximum Likelihood Estimates of the Cobb-Douglas Stochastic Production and Cost Frontier Models

Stochastic Production Frontier Model (SPFM)				Stochastic Cost Frontier Model (SCFM)			
Variable	**Coefficient**	**Std. Error**	**Z value**	**Variable**	**Coefficient**	**Std. Error**	**Z value**
Constant	1.9219***	0.0756	25.4219	Constant	3.6153***	0.4586	7.8833
In (quantity of labour)	0.2879**	0.0280	13.8280	*In* (cost of labour)	4.1224***	0.6374	6.4675
In (quantity of fertiliser)	0.5049**	0.2005	2.5182	*In* (cost of fertiliser)	0.5021***	0.0448	11.2076
In (quantity of agrochemicals)	-0.1388*	0.0726	-1.9118	*In* (cost of agrochemicals)	-3.6052***	0.6368	-5.6614
In (cost of capital)	0.0498	0.0801	0.6225	*In (cost of capital)*	0.1049***	0.0033	31.6122
				In (Output)	0.3040***	0.0205	14.8293
Model Summary							
Sigma	0.4921***	0.0463	10.6285	Sigma	0.1129***	0.0100	11.2900
Gamma	0.6699***	0.0612	10.9461	Gamma	0.9100***	0.0193	47.1503

	Log-Likelihood ratio test of model fitness for SPFM				Log-Likelihood ratio test of model fitness for SCFM			
	Likelihood	Df	Chi-sq.	P-value	Likelihood	Df	Chi-sq.	P-value
No inefficiency OLS model	-571.38				1475.7			
Error component frontier SFA model	-561.40	1	19.961	3.9^{e-06}***	1511.3	1	71.103	2.2^{e-16} ***

Significance codes: '' 0.01 '**' 0.05 '*' 0.1***

Source: Field Survey, Inkoom (2019)

Thus, the null hypothesis of no significant inefficiency effect (technical, economic, and allocative) in cocoa production is rejected in favour of the alternative.

Furthermore, the estimated sigma coefficients of 0.4921 for the production frontier and 0.1129 for the cost frontier which was found to be significantly different from zero, suggesting a good fit of the models and the correctness of the specified distributional assumptions respectively. In addition, the estimated gamma coefficients of 0.6699 for the production frontier and 0.9000 for the cost frontier indicates the presence of inefficiency effect and this suggests that technical, economic, and allocative inefficiencies are significant in explaining the variability in farm-level productivity among cocoa farmers in Ghana. Given this, the study failed to accept the assumption that there were no inefficiency effects (technical, allocative, and economic) in cocoa production. Theoretically, gamma picks a value between zero and one, indicating the importance of the inefficiency term. A value of zero means that the inefficiency term u is irrelevant or absent. On the other hand, if gamma is equal to one, then the noise or stochastic term v is completely irrelevant and that inefficiency (i.e., Technical, and economic, and inferably allocative inefficiencies) accounts for all the observed deviation from the production or cost frontier (Henningsen, 2019; Inkoom & Micah, 2017). Drawing from this, the estimated gamma coefficient of 0.6699 and 0.9000 for both production and cost frontier models implies that both inefficiency and stochastic noise effects are important in explaining any observed deviations from the production and cost frontiers. Nonetheless, inefficiency effects are considered the most important factor. Further probing of the gamma values using the decomposition procedure as suggested by Coelli *et al*. (2005) and demonstrated in R Programming Environment by Henningsen (2019) revealed that about 95 percent of the observed total inefficiency variance is attributable to technical and cost inefficiencies effect. The stochastic noise effect accounted for about 5 percent of the total variance.

The result from the stochastic production frontier model shows that the estimated output elasticity coefficient was positive for labour (man-day/ha), fertiliser (kg/ha) and capital (Gh¢/ha), but negative for pesticide (litre/ha). This suggests that the estimated production function is monotonically increasing for labour, fertiliser, and capital inputs, but decreasing for pesticide input. Furthermore, it was observed that except for capital input, all the three other input variables were significant in defining the production function. This implies that for any meaningful productivity growth in cocoa production, optimal and efficient use of labour, fertiliser and agrochemicals are critical. In technical terms, the results suggest that a percentage increase in fertiliser and labour inputs causes a marginal increase of 0.5049 percent and 0.2879 percent in the farm-level productivity of cocoa farmers. This observation tends to suggest there is some level of optimal allocation of labour and fertiliser inputs by farmers. On the other hand, a percentage increase in agrichemical inputs may lead to a marginal decrease of 0.1388 percent in the farm-level productivity of cocoa farmers. This suggests a potential misallocation or excessive use of agrochemicals by farmers. Thus, a radial reduction in agrochemical application to an optimal level will lead to a positive output elasticity of production. Furthermore, the scale elasticity was estimated to be 0.9814, which suggests that output growth was increasing but at a decreasing rate. This consequently implies that the productivity response was less proportionate to marginal increases in the variable inputs. Accordingly, ensuring efficient and optimal use of labour, fertiliser, capital, and agrochemical per hectare of land at the given technology can significantly increase productivity in cocoa production. The observed productivity impact from the estimated output elasticities associated with labour, fertiliser and agrochemical inputs application as presented in Table 6.1 on cocoa farmers productivity potential further advance empirical supports to other study findings on the productivity impact of labour, fertiliser, and agrochemicals in cocoa production (Danso-Abbeam & Baiyegunhi, 2020; Onumah *et al*., 2013; Danso-Abbeam, Aidoo, & Ohene-Yankyera, 2012; Aneani *et al*., 2011).

For the cost frontier model, Table 6.1 reveals that the estimated cost elasticity coefficients were all non-negative for Labour, fertiliser, and Capital except for agrochemical. This means that the estimated cost function is monotonically non-decreasing with respect to input price of labour, price of capital, and price of fertiliser, but decreasing with respect to the price of agrochemicals. Furthermore, the coefficient of the output quantity was non-negative, suggesting that the cost function is monotonically non-decreasing in output quantities. Again, the result reveals that the coefficients of the explanatory variables in the cost frontier model were all significant. The estimated positive cost elasticities of the price of labour, price of capital, and price of fertiliser imply that a percent increase in the prices of labour, capital and fertiliser may lead to a marginal increase in the total cost of production by a margin of 4.1224 percent, 0.5021 percent, and 0.1049 percent respectively. This empirical evidence on the cost implication of increases in the prices of production inputs is consistent with finding by Obeng and Adu (2014) on cost efficiency in cocoa production. Furthermore, the estimated negative coefficient of agrochemical, suggests the total cost of production decreases by a margin of 0.3040 percent as the unit cost share of prices of agrochemical increases. This result is not surprising given the fact that the mass spraying programme for pest and disease control initiated by the government has significantly reduced the overall cost burden of farmers in control pests and diseases on their farms. Again, the estimated positive coefficient of output quantity reflecting the cost flexibility, suggests that a percent increase in output contributes to the marginal increase in the cost build-up by a margin of 0.3040 percent. The observed positive relationship between output and cost of production again affirms the findings of Obeng and Adu (2014). Following the cost flexibility concept, an inverse of 0.3040 gives an elasticity of size value of 3.2895. This means that achieving a cost minimisation of one percent increases the output quantity of cocoa by 3.2895 percent.

6.3 Characterising the Technical Efficiency, Allocative Efficiency and Economic Efficiency among farmers

Figure 6.1 presents summary statistics of the farm-level efficiency distribution for cocoa farmers. Following the duality concept, the study estimated the Cobb Douglas stochastic production and cost frontier models which provided the theoretical soundness to decompose the efficiency estimates into the respective efficiency components (i.e., technical, allocative, and economic) as proposed by Farrell (1957). The decomposition procedure follows that of Coelli *et al*. (2005) and Henningsen (2019). The general outlook from the efficiency estimates shows that farmers were not fully efficient technically, allocatively and economically. This suggests the presence of technical, allocative, and economic inefficiencies in cocoa production which confirms other study findings on the estimation of farm-level efficiency in cocoa production in Ghana (Aneani *et al*., 2011; Onumah *et al*., 2013; Danso-Abbeam, & Baiyegunhi, 2020). Following the quartile distribution principle, the efficiency score was quarterised. The quarterisation led to four efficiency profile categories. The description of the categories is as follows: low-efficiency profile (0 – 0.24), moderately low-efficiency profile (0.25 – 0.49), moderately high-efficiency profile (0.51 – 0.74), and High-efficiency profile (0.75 – 1.00).

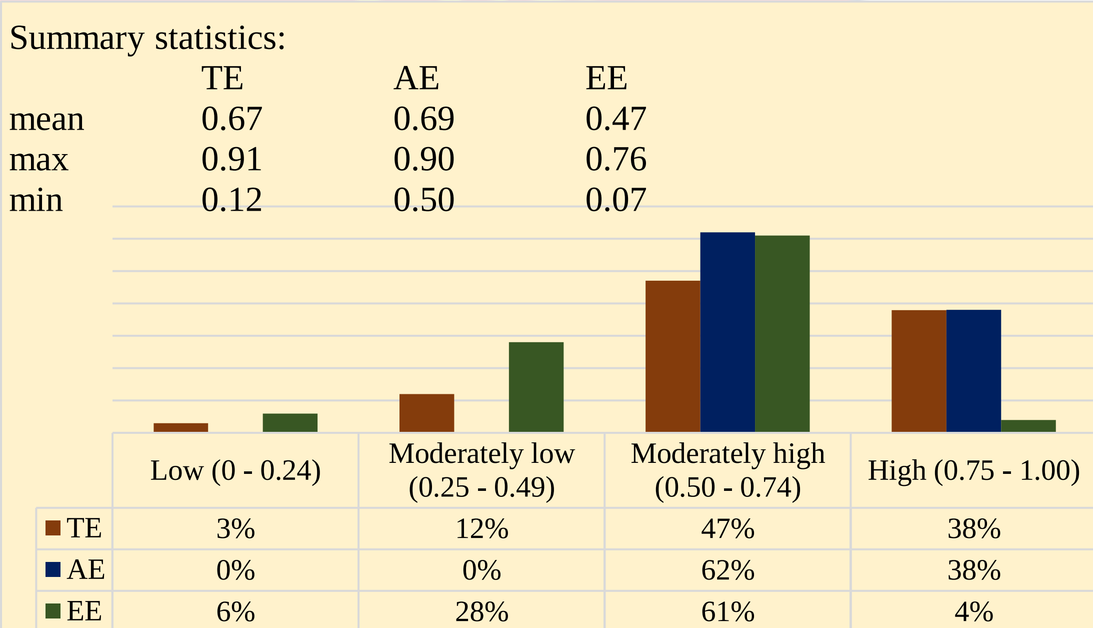


Figure 6.1: Distribution of Farmers According to their Efficiency Scores

Source: Field survey, Inkoom (2019)

The estimated technical efficiency scores ranged between 0.12 to 0.91 with a mean technical efficiency score of 0.67. The mean estimate indicates a 67 percent technological efficiency, which does suggest a moderate ability of farmers in achieving the minimal input combination to produce maximum output. The mean estimate of technical efficiency further suggests that farmers were about 0.33 (i.e., 33 percent) below the efficient and optimal frontier that maximises output and utility (i.e., profit). This means that there is about 33 percent technical inefficiency in cocoa production. In addition, the percentage distribution shows that the majority of the farmers exhibited a moderate to high technical efficiency level. Furthermore, the result as indicated in Figure 6.1 shows that the estimated average allocative efficiency score was 0.69 with a range of 0.50 to 0.90. The mean estimate indicates a 69 percent resource-use efficiency among cocoa farmers, which does suggest a moderate ability of farmers in producing maximum output using a cost-minimising input proportion.

Again, the mean estimate of allocative efficiency indicates that farmers were about 0.31 (i.e., 31 percent) below the efficient and optimal frontier that minimises cost and utility (i.e., profit maximisation). This implies that there is about 31 percent allocative inefficiency in cocoa production. In addition, the percentage distribution shows that most of the farmers exhibit a moderate to high level of allocative efficiency. A further look at Figure 6.1 shows that the economic efficiency scores ranged from 0.07 to 0.76 with an average economic efficiency score of 0.47. The mean estimate indicates a 47 percent technological and resource-use efficiency among cocoa farmers. This by inference suggests a moderate ability of farmers to produce maximum output from a minimal input combination at the least cost possible. The mean economic efficiency again suggests that farmers were about 0.53 (i.e., 53 percent) below the efficient and optimal frontier that minimises cost and utility (i.e., profit maximisation). This suggests that the level of economic inefficiency in cocoa production was about 53 percent. In other words, farmers' ability to maximise output with minimal input combination at the least cost possible was reduced by 53 percent point deviation.

Comparing the distribution of the three efficiency estimates, the technical and allocative efficiencies signal a good productive performance among cocoa farmers. However, bringing on economic efficiency suggests otherwise. Accordingly, it can be concluded that a farmer may be technically and/or allocatively efficient but might not be economically efficient. Consequently, for a much effective assessment of farm-level efficiency, estimating economic efficiency would give a better representation. Having estimated the farm-level efficiencies, the study went on to investigate the factors that significantly explain variation in the farm-level efficiencies among farmers. This was then under the Heckit treatment effect model that estimates the effect of climate smart adaptation on the efficiency of production. In view of this, the result is subsequently discussed in chapter 7, Section 7.4 to avoid repetition.

6.4 Characterising the Household Food Security status among Cocoa Farmers

The fourth research objective evaluated the food security situation among cocoa farming households. Given the multidimensional nature of food security, the study followed a multidimensional estimating approach centring on the FAO food security framework. This captures four food security dimensions: food availability, food accessibility, food utilisation and food stability. The results of the food security analysis are presented in Table 6.2. The food availability dimension was measured using a household food consumption scale. Household food accessibility was captured using the household food insecurity access scale. The household food utilisation was assessed using the household dietary diversity scale. Again, household food stability was captured using the household coping strategy scale.

Table 6.2: Distribution of Farmers based on their Household Food Security Situation

	A	B	C	D	E	F	G
Food Security Dimension or indicator	**Food Insecured (0.0 – 0.24)**	**Marginally Food Insecured (0.25– 0.49)**	**Marginally Food secured (0.50 – 0.74)**	**Food secured (0.75 – 1.0)**	**Mean HFS index (*p*)**	**Mean HFIV index (1-*p*)**	**Percentage contribution to food insecurity**
Household Food Availability (HFAV)	**4.2%**	**37.6%**	**39.2%**	**23.7%**	**0.5682**	**0.4318**	**25.43% Rank=3**
Household Food Accessibility (HFAB)	**5.2%**	**30.8%**	**18.8%**	**45.2%**	**0.6481**	**0.3519**	**20.73% Rank=4**
Household Food Utilisation (HFUT)	**-**	**50.0%**	**45.1%**	**4.9%**	**0.5568**	**0.4432**	**26.11% Rank=2**
Household Food Stability (HFSB)	**11.7%**	**35.0%**	**36.5%**	**16.80%**	**0.5298**	**0.4702**	**27.73% Rank=1**
The Composite multidimensional index	**0.56%**	**30.34%**	**62.20%**	**6.90%**	**0.5757**	**0.4243**	

Model summary: Food security measurement, does measuring approach matter? — Unidimensional vs Multidimensional

ANOVA test	**Df**	**Sum Sq.**	**Mean Sq.**	**F value**	**P-value**
Food security dimension	3	5.591	1.86361	45.259	< 2.2e-16 ***
Residuals	2876	118.425	0.04118		

Levene's test of homogeneity of variance DF=3 F value =0.2347 P value = 0.8723

Shapiro-Wilk normality test W= 0.91389 p-value = 0.2216

Posthoc Test for the source of differences: Tukey's Honest Significant Difference test

Contrast	Estimate	SE	Df	t-value	P-value
HFAV - HFAB	-0.0799***	0.0107	2876	-7.467	<.0001
HFAV - HFUT	0.0114	0.0107	2876	1.068	0.7089
HFAV - HFSB	0.0385***	0.0107	2876	3.599	0.0018
HFAB - HFUT	0.0913***	0.0107	2876	8.535	<.0001
HFAB - HFSB	0.1183***	0.0107	2876	11.066	<.0001
HFUT - HFSB	0.0271**	0.0107	2876	2.531	0.0555

*Significance codes: '***' 0.01 '**' 0.05 '*' 0.1*

Source: Field Survey, Inkoom (2019) n = 720

The information obtained from these four scales was then used to compute the Household Food Security Index (HFS index) on a continuous scale of 0 (food insecured) to 1 (food secured) as discussed under section 3.15.1 in chapter three. A movement from 0 to 1 implies increasing household food security, hence decreasing vulnerability to household food insecurity. The reverse movement from 1 to 0 implies increasing vulnerability to household food insecurity, hence decreasing household food security.

Based on the HFS index computed, households were categorised into four main food security groups. That is, food insecured category, marginally food insecured category, marginally food secured category and food secured category. This was done based on the quarterisation of the estimated HFS index. The four categories were then assigned a colour system indicating the severity of food insecurity or degree of food security as observed among cocoa farmers. The results generally show significant variability in the distribution of farmers within the food security groupings. It was observed that there is some convergence among the food security dimensions as to the true state of household food (in)security among cocoa farmers. The result indicates that on the food availability dimension, about 39.2 percent of the farmers were marginally food secured and 23.7 percent were food secured. It was further noted that about 37.6 percent of the farmers were marginally food insecured and 4.2 percent were food insecured. The mean HFS index of 0.5682 associated with the food availability dimension suggests that when it comes to household food availability, farmers are marginally food secured. This result indicates that the average cocoa farmer has a marginal ability to ensure adequate food supply on a regular basis for effective household food consumption. From column F of

Table 6.2, the HFIV index with respect to the food availability dimension was estimated to be 0.4318, indicating that the vulnerability or probability of the average farmer experiencing a food insecurity situation from the food availability perspective is about 43 percent. This suggests that although farmers may be marginally food secured in the short-to-medium term, their vulnerability to severe food insecurity situation in the medium-to-long term may always worsen due to the potential decline in the adequacy of regular food supply and availability. The observed food insecurity vulnerability of cocoa farmers with respect to food availability affirms other study findings where lack of regular and adequate food available has caused farmers to experience food insecurity tendency (Akukwe, 2020; Dei Antwi *et al*., 2018; Mustapha, Mohammed, & Abdul Fatahi, 2016; Nyamekye, 2015; Osei *et al*., 2013).

Furthermore, for the food accessibility dimension, it was observed that about 18.8 percent of the farmers were marginally food secured and 45.2 percent were food secured. Additionally, about 30.8 percent of the farmers were marginally food insecured and 5.2 percent were food insecured. The mean HFS index associated with food accessibility was observed to be 0.6481, suggesting a marginally food secured situation. This by inference means that the average cocoa farmer has a marginal ability in ensuring physical, social, and economic access to appropriate food for a nutritious diet at all times. As reported in column F of Table 6.2, the HFIV index with respect to the food accessibility dimension was estimated to be 0.3519, indicating that the vulnerability or probability of the average farmer experiencing food insecurity situation from the food accessibility perspective is about 35 percent. This suggests that although farmers may be marginally food secured in the short-to-medium term, their vulnerability to severe food insecurity situation in the medium-to-long terms may worsen due to the potential decline in the adequacy of physical, social, and economic access to sufficient food at all times. The observed food insecurity vulnerability of cocoa farmers with respect to food accessibility advance empirical support to other study findings where lack of regular and adequate access to food has caused farmers to experience food insecurity tendency (Dei Antwi *et al*., 2018; Hussein *et al*., 2018; Aidoo, Mensah, & Tuffour, 2013).

In addition, the results revealed that, when it comes to the food utilisation dimension, about 45.1 percent of the farmers were marginally food secured and 4.9 percent were food secured. The remaining 50 percent were found to be marginally food insecured. Again, the mean HFS index was found to be 0.5568 and this suggests that, on average, farmers were marginally food secured. With this, it can be inferred that farmers have a marginal ability in ensuring diversity in food availability and consumption at all times. This could largely mean that the diversity and quality of food available to farm households may not be adequate in providing the needed nutritional requirement for a healthy and quality life. From column F of Table 6.2, the HFIV index with respect to the food utilisation dimension was estimated to be 0.4432, indicating that the vulnerability or probability of the average farmer experiencing food insecurity situation from the food utilisation perspective is about 44 percent. This suggests that although farmers may be marginally food secured in the short-to-medium term, their vulnerability to severe food insecurity situation in the medium-to-long terms may worsen due to the potential decline in the adequacy of diversity in food availability and consumption. The observed food insecurity vulnerability of cocoa farmers with respect to food accessibility advance empirical support to other study findings of how inadequacy in household dietary diversity has caused farmers to experience higher food insecurity tendency (Huluka & Wondimagegnhu, 2019; Adjimoti & Kwadzo, 2018; Ayenew, Biadgilign, Schickramm, Abate-Kassa, & Sauer, 2018).

Further, the coping strategy employed by cocoa farmers in the face of food stress, shock, and budget deficit was used as a proxy measure to estimate household food stability among cocoa farmers. The findings as presented in Table 6.2 revealed that about 36.5 percent of the farmers were marginally food secured and 16.8 percent were food secured. In addition, the results point out that about 35 percent of the farmers were marginally food insecured and 11.7 percent were noted to be food insecured. In addition, the estimated mean HFS index of 0.5298 suggests a marginally food secured situation among farmers according to the household food stability perspective. This by extension suggests that farmers exhibit a marginal ability to coping with food stress, shock, and budget deficit. As shown in column F of Table 6.2, the HFIV index with respect to the food stability dimension was estimated to be 0.4702. This suggests that the vulnerability or probability of the average farmer experiencing food insecurity situation from the food stability perspective is about 47 percent. It can thus be argued that, although farmers may be marginally food secured in the short-to-medium term, their vulnerability to severe food insecurity situation in the medium-to-long terms may worsen due to the potential decline in the adequacy in the stability of food availability, accessibility, and utilisation at all time. The observed food insecurity vulnerability of cocoa farmers with respect to food accessibility advance empirical support to other study findings instability in food availability, accessibility and thereby utilisation has caused farmers to experience food insecurity tendency (Mutea *et al*., 2019; Adjimoti & Kwadzo, 2018; Kuwornu, Suleyman, & Amegashie, 2013).

On the multidimensional level, the estimated HFS indexes show that there seems to be some convergence among the four individual food security dimensions on the actual food security situation among cocoa farmers. To verity this, the composite multidimensional household food security index (MHFS index) was computed. The results as portrayed in Table 6.2 revealed that about 62.2 percent and 6.9 percent of the farmers were marginally food secured and food secured respectively. It was further observed that about 30.34 and 0.56 percent were noted to be marginally food insecured and food insecured respectively. The mean MHFS index was estimated to be 0.5757, suggesting that on the aggregate level farmers are marginally food secured. This affirms the convergences among the four food security dimensions. Additionally, the multidimensional household insecurity vulnerability index (MHFIV index) was computed as (i.e., $MHFIV_{index} = (\sum_{n=1}^{n} HFIV_{index})/n$). The estimated MHFIV index of 0.4243 as reported in column F of Table 6.2 indicates that the vulnerability or probability of the average farmer experiencing a food insecurity situation from the multidimensional perspective is about 42 percent. This suggests that although farmers may be marginally food secured in the short-to-medium term, their vulnerability to severe food insecurity situation in the medium-to-long terms may worsen due to the potential decline in the adequacy of food availability, accessibility, utilisation, and stability at all times.

Having observed that cocoa farmers in the medium-to-long term may be vulnerable to severe food insecurity situation as suggested from the data, it became necessary to answer the question of whether the measurement approach does matter in food security analysis. That is, does the choice of multidimensional approach as against a unidimensional approach appropriate for the analysis of food security matter? To do this, an ANOVA test was carried out to see whether there exists a significant difference in the mean HFI index estimated for the four food security dimensions. To check whether the dataset pass for the ANOVA analysis, Levene's test for homogeneity of variance and Shapiro-Wilk normality test was done. As indicated in Table 6.2, the high p-values associated with both tests indicate the dataset meets the homogeneity of variance and normality assumptions. Consequently, the ANOVA test of equality of means was carried out. The significant F value of the ANOVA test result as portrayed in Table 6.2 suggests that there is a significant difference among the mean HFS index for the four food security dimensions. This implies that in assessing household food security situations, the measuring approach does matter. This by extension suggests that unidimensional measures tend to portray different food security situation, depending on which food security dimension is used. It can, therefore, be argued that a multidimensional measurement approach gives a better representation of the actual food insecurity situation among farmers. Having observed the presence of significant differences in the means HFS index, a posthoc test, specifically the Tukey's Honest Significant Difference test was carried to identify where the difference exists. The posthoc test for the source of the difference revealed that, except for the paired-wise comparison between food availability and food utilisation, the paired-wise comparison between the other food security dimensions showed a significant difference.

To ascertain the weighting effect of each food security dimension on the overall multidimensional food security status of cocoa farmers, the percentage contribution of each of the food security dimensions to the food insecurity problem was estimated. As shown in column G of Table 6.2, food availability contributed about 25.43 percent to the food insecurity problem; food accessibility contributed about 20.73 percent to the food insecurity problem; food utilisation contributed about 26.11 percent to the food insecurity problem; food stability contributed about 27.73 percent to the food insecurity problem. From this, it can be concluded that in preferring solutions to address household food insecurity, the order of preference should be as follows; food stability dimension should rank first, followed by food utilisation, food availability and food accessibility in that order. Drawing upon the estimated mean HFS index associated with the four dimensions, adopting a multidimensional estimation approach gives an accurate and comprehensive representation of household food (in)security. This is because the approach presents an opportunity to properly identify where the danger lies and how to develop appropriate policy interventions to efficiently build farmers' resilience and reduce their vulnerability and exposure to household food insecurity. As a further analysis, potential factors that explain the food security situation was captured under the Heckit treatment effect model, the results of which are discussed in chapter 7 under section 7.4.

6.5 Chapter Summary

The chapter presented the discussed results on the characterisation of farmers based on their estimated technical efficiency, allocative efficiency, economic efficiency, and household food security situation. The result showed that farmers exhibited a significant level of technical, allocative, and economic inefficiencies in production. Again, most of the farmers were found to be marginally food secured. The next chapter discusses the results on the food security implication of the connect between extension service quality, climate smart adaptation and efficiency of production among cocoa farmers.

CHAPTER SEVEN

CONNECTS BETWEEN EXTENSION SERVICE QUALITY, CLIMATE SMART ADAPTATION, EFFICIENCY OF PRODUCTION AND FARM HOUSEHOLD FOOD SECURITY

7.1 Introduction

The core of the current study was to estimate the food security implication of the nexus between extension service quality, climate smart adaptation, and efficiency of production among cocoa farming households in Ghana. Accordingly, by following a sequential causal framework under a transitivity rationale, the Heckit treatment effect model was estimated to test the null of food security implication of the connects between extension service quality, climate smart adaptation, and efficiency of production. The empirical application of the Heckit treatment effect model followed the hypothesised causal link relationships as postulated in the conceptual framework (*see, Figure 2.2*). To create a natural condition for the efficient application of the Heckit treatment effect model, it was conditioned on the farmers' awareness of the occurrence of climate change and access to extension contact. This helped isolate the direct causal effect of the treatment variable on the outcome variable as well as making a justified case for an efficient and unbiased causal effect estimate (Greene, 2012; Heckman, 1979, 2005; Scott, 2019).

The Heckit treatment effect model contains two model results: selection equation (predicts determinants of selection into treatment) and outcome equation (predicts the effect of treatment variable on outcome variable). Again, the treatment variable serves as a policy indicator and that its coefficient shows how much the outcome variable will increase or decrease if we can manipulate the policy indicator. The results discussed here include analysis of the causal effect of extension service quality on the adoption of CSA strategies, the causal effect of CSA on the efficiency of production, and the causal effect of efficiency of production on household food security.

7.2 Heckit Treatment Effect Model Results on the Causal Effect of Extension Service Quality on the Adoption of Climate Smart Adaptation (CSA)

It is widely recognized that increasing access to extension service is critical for stimulating higher technology adoption rates among farmers. However, the current study assumed that access to extension service when limited to quantitative increases may not do the magic. Hence, the need to focus on delivering quality extension service due to its intrinsic influence on farmers' service utility. Accordingly, the Heckit treatment effect model was estimated to evaluate the direct causal effect of improved extension service quality on the adoption of CSA strategies among cocoa farmers. The model result is presented in Table 7.1 and it contains results on the selection equation which describes the factors that influence the likelihood that a farmer will self-select into treatment (i.e., perceiving higher service quality or otherwise); and the outcome equation which measures how much adoption of CSA technologies will rise or fall with respect to a farmer self-selecting into treatment (i.e., perceiving higher extension service quality—defined by above-average service quality perceivers).

Following the binomial distribution theorem or the bivariate normality, the study based on the average count of CSA measures to group farmers into above-average service quality perceivers and below-average service quality perceivers as an indicator of treatment or otherwise (i.e., treatment variable).

Accordingly, the study assigned above-average service quality perceivers to be the treatment group as they exhibited a high level of perceived service quality and below-average service quality perceivers to be the control group as they exhibit a low level of perceived service quality. The treatment group was assigned a code of 1 and the control group was assigned a code of 0. The model result as presented in Table 7.1 demonstrates the potential impact of improvement in extension service quality on the adaptation decision of farmers with respect to the adoption rate of CSA technologies or measures.

Table 7.1: Heckit Treatment Effect Model Result on the Causal Effect of Extension Service Quality on the Adoption Of Climate Smart Adaptation Technologies

Variables	Coefficient	Std. Error	T value
Selection equation:			
Intercept	-1.1181***	0.2824	-3.958
Sex	0.1753*	0.1048	1.673
Age	-0.0159**	0.0053	-2.955
Education	0.0591***	0.0101	5.876
FBO membership	0.3264***	0.0803	4.063
Farming experience	0.0404***	0.0074	5.467
Frequency of extension contact	0.0872***	0.0185	4.703
Outcome equation			
Intercept	1.3129***	0.1312	10.000
Treatment (extension service quality)	0.7151***	0.0624	11.443
Perceived rainfall variability	0.0178**	0.0077	2.313
Perceived temperature variability	0.0283***	0.0091	3.096
Perceived impact of climate change	0.0641***	0.0077	8.300
Awareness of CSA options are adaptation response	1.4446***	0.0561	25.749
Risk perception towards CSA	-0.1896***	0.0358	-5.288
Sex	0.0345	0.0424	0.815
Age	0.0120***	0.0019	6.114
Education	0.0187***	0.0040	4.622
Farming experience	0.0102***	0.0029	3.517

Model summary:

	Coefficient	Std. Error	t value	P-value
Sigma	0.4814***	0.0200	24.02	$<2^{e-16}$
Rho	0.7863***	0.0489	16.07	$<2^{e-16}$

Significance codes: '' 0.01 '**' 0.05 '*' 0.1***

Source: Field survey, Inkoom (2019)

To validate the robustness and efficiency of the model estimates, a test of the model fitness was carried out. Theoretically, the test statistic that is used to validate the superiority of the Heckit endogenous treatment effect model over the traditional two-stage regression model is the rho(ρ) estimate. For an unbiased and efficient estimation, the Heckit endogenous treatment effect model assumes that the degree of correlation (ρ or rho) between the two-error term from the selection equation and outcome equation is non-zero. As such, a test of $\rho = 0$ against $\rho \neq 0$ was carried out to evaluate whether the use of the Heckit endogenous treatment effect model for the joint likelihood estimation of the selection equation and outcome equation was appropriate and fit the dataset. The model summary as shown in Table 7.1 shows that the estimated rho and sigma statistics were significantly different from zero. This confirms the superiority of the Heckit endogenous treatment effect model in giving robust and efficient results to the dataset. Again, this indicates that the model estimation was appropriate and that the result is an unbiased estimate of the true treatment effect. Consequently, the model results from the Heckit endogenous treatment effect model can be accepted to be robust and efficient.

Furthermore, the estimated rho value confirms that there is a direct causal effect of improved extension service quality on climate smart adaptation as argued in the conceptual framework (*see Figure 2.2*). Based on this, the fourth research hypothesis was evaluated. The highly and statistically significant coefficient estimate of Rho (0.78) suggests that the direct causal effect of extension service on the adoption of CSA technologies does exist at a 1 percent significant level. This, therefore, confirms the presence of self-selectivity and endogeneity bias problems in the dataset. Accordingly, the study failed to accept the null hypothesis that (i.e., $\rho(H_0: \rho = 0)$—*"Quality of extension service does not significantly influence the adoption of CSA practices among farmers"*) in favour of the alternative hypothesis (i.e., $\rho(H_1: \rho \neq 0)$—*"Quality of extension service significantly influence the adoption of CSA practices among farmers"*).

From the results, as portrayed in Table 7.1, it was evident that there is an endogenous treatment effect relationship between improved extension service quality and adoption of CSA practices among cocoa farmers. From the result, the estimated coefficients in the selection equation show that the predicted probability of all the predictor variables was significant. For instance, the result indicates that the probability of selection into treatment (i.e., perceiving a higher extension service quality) is positively and significantly influenced by the conditional factor, access to extension service. This means that increases in the frequency of extension contact have the likelihood of positively influencing the extent of extension service quality received by farmers. Consequently, a pragmatic increase in the frequency of extension service delivery that centres on improvement in extension service quality with respect to the five dimensions would have a sequential multiplier effect on farmers' adaptation decisions with respect to the adoption of more CSA technologies.

In addition, the estimated positive coefficient of sex indicates that male farmers were more likely to self-select into treatment, suggesting that male farmers were more likely to receive quality extension service than female cocoa farmers. This could be attributed to the socio-economic and cultural environment that give better opportunities to male farmers to access input resources. Again, the negative coefficient of age suggests that the older farmers were less likely to self-select into treatment. This probably could mean that the ageing effect hinders their ability to access improved quality extension services. Furthermore, the result as portrayed in Table 7.1 shows that the estimated coefficient of education was positive, suggesting that receiving a higher level of education increases the likelihood of farmers self-selecting into treatment. This could be attributed to the added ability to read and independently understand the extension information delivered to them. It was further noted that membership to farmer-based organisations positively influences the likelihood of farmers self-selecting into treatment. This could be attributed to the fact that by belonging to an FBO, farmers can obtain information and ideas from colleagues that put them in a better position to correctly appraise the kind of extension service received.

Again, the estimated positive coefficient of farming experience suggests farmers with more years of experience were more likely to self-select into treatment. This could be attributed to the added advantage of experiential knowledge and learning which give them the ability to accurately assess the quality of extension service delivered to them. In summary, the important predictors of extension service quality as identified have significant implications for policy direction on what to do to trigger access to higher and improved service quality by farmers. Thus, it is imperative that to enhance the probability of selection into treatment (i.e., farmers perceiving a higher quality of extension service), the importance of these variables is taken into consideration. This has proven consequential effects on the adoption decisions of farmers with respect to CSA technologies. The observed findings in this study support other study findings (Min & Khoon, 2013; Christia & Ard, 2016; Abdel-Ghany & Abdel-Salam, 2012; Abdel-Ghany & Diab, 2015).

Having established the factors that significantly explain selection into treatment, the potential treatment effect of improved extension service quality on the adoption of CSA strategies was presented and the result is contained in the outcome equation as presented in Table 7.1. The result shows that the treatment variable (extension service quality) has a significant direct causal effect or impact on the adoption of CSA technologies among cocoa farmers. In other words, the outcome equation result suggests that improvement in the quality of extension service delivered to farmers has a significant positive impact on the adoption rate of CSA technologies. Hence, as the quality of extension service increases, the adoption rate of CSA technologies increases. The estimated positive coefficient of the treatment variable suggests that farmers who perceived higher extension service quality are more likely to adopt more CSA technologies as adaptation responses to climate change. In fact, the estimated treatment coefficient of 0.7151 implies that improvement in the quality of extension service has about 72 percent likelihood of enhancing the adoption rate of CSA technologies. The significant treatment effect of improved quality of extension service on the climate smart adaptation behaviour as observed from this study lends empirical credence to previous studies that have reported that access to improved extension service delivery significantly influences climate smart adaptation decisions of farmers (Issahaku & Abdulai, 2020; Wekesa, Ayuya, & Lagat, 2018; Etwire, Al-Hassan, Kuwornu, & Osei-Owusu, 2013).

Benchmarking the estimated coefficient of the treatment variable to the average service quality index shows that farmers with an above-average service quality perception score are about 50 percent [i.e., (0.7151*0.7) *100] more resilient to climate change effect than their counterparts. What this means is that the CSA adoption rate among these farmers is about 50 percent higher than their counterparts. This in effect means that if the appropriate mechanism is put in place for effective and quality extension service delivery, it will simulate the propensity of increasing the adoption rate of CSA technologies among cocoa farmers, all other things being equal. The statistically significant causal effect of extension service quality as established in this study underscores the important role of improved quality extension service coupled with the mainstreaming of climate smart adaptation strategies in addressing the livelihood security impact of the persistent low farm-level productivity and the adverse consequence of climate change among cocoa farmers. This result, therefore, provides an economic rationale for policy interventions not to just concentrate on increasing access to extension service, but to focus much attention on ensuring the provision of higher and improved quality extension service to farmers.

Furthermore, the outcome equation results show that all the climate change conditional variables were significant in influencing the adoption of CSA strategies among cocoa farmers. For instance, the positive coefficient of perceived variability in rainfall suggests that as perceived variability in rainfall increases (especially, the persistent decrease in rainfall and increases in its unpredictable pattern) the propensity of farmers adopting more CSA strategies as adaptation responses increases by a margin of 0.0178. Furthermore, the positive coefficient of perceived variability in temperature suggests that as perceived variability in temperature increases (i.e., persistent increase in temperature), the tendency of farmers adopting more CSA strategies as adaptation responses increases by a margin of 0.0283. Again, the estimated positive coefficient of the perceived impact of climate change suggests that as the perceived impact of climate change increases, the proclivity of farmers adopting more CSA strategies also increases by a margin of 0.0641. Additionally, the coefficient of farmers' awareness of available CSA strategies was estimated to be positive. This suggests that as farmers become more aware that the available CSA strategies are indeed adaptation mechanisms to climate change, their inclination to adopt also increases by a margin of 1.4446. The results also show that the estimated coefficient of farmers risk perception towards investment in CSA strategies as expected was negative. This suggests that as the perceived riskiness associated with investing in CSA increases, the propensity of farmers adopting more CSA practices decreases by a margin of 0.1896.

Considering the farmer-specific variables introduced as control variables in the outcome equation, the result indicates that age, education, and years of farming experience have a significant positive influence on the adoption of CSA technologies among cocoa farmers. This finding supports findings of other studies on the influences of age, education, and farming experience on climate smart adaptation decisions among farmers (Denkyirah *et al*., 2017; Selase, Xinhai, & Worlanyo, 2017; Khatri-Chhetri, Aggarwal, Joshi, & Vyas, 2017; Li, Juhasz-Horvath, Harrison, Pinter, & Rounsevell, 2017; Ehiakpor, Danso-Abbeam, & Baah, 2016; Ndamani & Watanabe, 2016; Barnes, Islam, & Toma, 2013). The observed result suggests that aged farmers were more likely to adopt more CSA technologies as measures to mitigate the impact of climate change. Thus, a unit increase in the age of farmers may lead to a marginal increase in the likelihood of adopting more CSA technology by a margin of 0.0120. This could probably be attributed to the potential advantage of experiential knowledge that comes with age. This was further corroborated by the observed positive influence of years of farming experience on the adoption of CSA technology. The observed positive effect of farming experience in principle implies that, as farmers acquire more experience due to a marginal increase in the years of farming, the likelihood of them adopting more CSA technologies would increase by a margin of 0.0102. The observed positive relationship between educational level and adoption of CSA technologies implies that when education level is increasing, adoption of CSA technologies is increasing too. Thus, educated farmers will be more likely to adopt more CSA technologies. Hence, providing more education on CSA technologies will yield a positive marginal benefit to farmers by influencing the proclivity of them adopting more CSA technologies by a margin of 0.0187.

From the counterfactual proposition, the significant positive rho estimates suggest that should farmers receive a higher level of improved quality of extension service, they will have a higher propensity to adopt more CSA strategies as adaptation responses to mitigate against the adverse consequences of climate change. On the other hand, a significant negative rho estimate implies that farmers will exhibit a low propensity of adopting more CSA strategies should they receive a low quality of extension service. With this, it can be concluded that a higher level of improved quality of extension service does have implications for improved climate change adaptation decisions among cocoa farmers. Having established the presence of endogenous treatment effect relationship between the selection equation and the outcome equation, and in following a transitivity rationale, the study proceeded to extend the argument to test the causal link between climate smart adaptation and efficiency of production in sequential order as hypothesized in the conceptual framework (*see Figure 2.2*). The results of which are discussed in Section 7.3 below.

7.3 Heckit Treatment Effect Model Results on the Causal Effect of Climate Smart Adaptation on Economic Efficiency, Technical Efficiency, and Allocative Efficiency

Having demonstrated that improved extension service quality has implications for mainstreaming climate smart adaptation strategies in cocoa production, it became apparent to test the sequential impact of improved adoption of CSA on the efficiency of production to comprehensively address the livelihood security impact of the persistent low farm-level productivity and the adverse consequence of climate change among cocoa farmers in Ghana. Generally, the use of innovative technologies in agriculture offers an opportunity for improving the productivity and income of farmers significantly. However, due to certain observable and unobservable characteristics, the productivity impact of technology adoption is often limited. Thus, conditional on farmers' awareness of the occurrence of climate change and access to extension contact, the Heckit treatment effect model was estimated to evaluate the potential and direct causal effect of the adoption of CSA strategies on the efficiency of production (i.e., technical, allocative, and economic).

The model result is presented in Table 7.2 and it contains results on the selection equation which describes the factors that influence the likelihood that a farmer will self-select into treatment (i.e., above-average adaptation—adopting higher count of CSA measures or otherwise); and the outcome equation which measures how much farm-level productivity, indicated by the efficiency of production will rise or fall with respect to a farmer self-selecting into treatment (i.e., above-average adaptation—adopting a higher level of CSA practices in the presence of climate change). Following the binomial distribution theorem or the bivariate normality, the study based on the average count of CSA measures to group farmers into above-average adapters and below-average adapters as an indicator of treatment or otherwise (i.e., treatment variable). Accordingly, the study assigned above-average adapters to be the treatment group as they exhibited a high adoption of CSA measures and below-average adapters to be the control group as they exhibit a low adoption of CSA measures. The treatment group was assigned a code of 1 and the control group a code of 0.

The model result as presented in Table 7.2 demonstrate the potential impact of an improved adoption rate of CSA technologies on the farm-level productivity growth (indicated by the efficiency of production). The model analysis was done at three levels by predicting the treatment effect of CSA on all three efficiency components (i.e., technical, allocative, and economic). This resultantly led to three selection equations and three outcome equations as presented in Table 7.2. The results of the three Heckit treatment effect models as presented in Table 7.2 is under the headings: Causal effect of CSA on TE, Causal effect of CSA on AE, and Causal effect of CSA on EE respectively. To validate the robustness and efficiency of the model estimates, a test of the model fitness was carried out. Theoretically, the test statistic that is used to validate the superiority of the Heckit endogenous treatment effect model over the traditional two-stage regression model is the rho(ρ).

Table 7.2: Heckit Treatment Effect Model Result on the Causal Effect of Climate Smart Adaptation on Technical, Allocative, and Economic Efficiencies

Variable	Effect of CSA on TE			Effect of CSA on AE			Effect of CSA on EE		
	Coeff.	SE	T value	Coeff.	SE	T value	Coeff.	SE	T value
Selection Equation:									
Intercept	-1.2049***	0.3525	-3.418	-1.1558***	0.3442	-3.358	-1.2803***	0.3522	-3.635
Sex	0.1070	0.1044	1.025	0.0998	0.1053	0.948	0.1111	0.1043	1.065
Age	0.0405***	0.0049	8.237	0.0393***	0.0049	7.960	0.0405***	0.0049	8.233
Education	0.0424***	0.0103	4.100	0.0381***	0.0100	3.796	0.0425***	0.0103	4.099
Frequency Extension contact	0.0614**	0.0250	2.452	0.0558**	0.0245	2.276	0.0614**	0.0251	2.445
Perceived impact of climate change	0.9024***	0.2075	4.348	0.3613*	0.2044	1.767	0.0610**	0.0266	2.428
Awareness of CSA strategies	0.9707***	0.2164	4.485	0.7541***	0.2029	3.716	0.9009***	0.2144	4.202
Outcome Equation:									
Intercept	-2.0363***	0.1430	-14.231	0.5829***	0.0235	-24.718	-2.5960***	0.1455	-17.831
Treatment (Use of CSA)	0.4164***	0.1029	4.046	0.4882***	0.1578	3.094	0.4838***	0.1095	4.416
CSA risk perception	-0.1387**	0.0636	-2.179	-0.0089	0.0101	-0.879	-0.1298**	0.0644	-2.014
Access to quality extension service	0.0300***	0.0092	3.244	0.0492***	0.0145	3.364	0.0258**	0.0093	2.754
Frequency Extension contact	0.1099**	0.0432	2.544	0.0662***	0.0178	3.719	0.0913**	0.0438	2.086
Sex	-0.0165	0.0450	-0.367	0.0077	0.0075	1.026	-0.0145	0.0458	-0.317
Age	-0.0087***	0.0028	-3.058	0.0013**	0.0004	2.769	-0.0092***	0.0029	-3.172
Education	0.0126**	0.0044	2.824	0.0025***	0.0007	3.455	0.0114**	0.0045	2.506
Farming experience	0.0051*	0.0027	1.881	0.0017	0.0435	0.039	-0.0050*	0.0027	-1.823
FBO membership	-0.0132	0.0385	0.344	-0.0015	0.0061	-0.255	-0.0138	0.0390	-0.354
Farm size	0.0336**	0.0121	2.783	-0.0017***	0.0019	-4.028	0.0410***	0.0123	3.331
Access to credit facilities	0.0111	0.0107	1.033	-0.0156**	0.0069	-2.266	0.0074	0.0110	0.675
Model Summary									
Sigma	0.5323***	0.0265	20.104	0.0885***	0.0046	19.216	0.5421	0.0282	19.198
Rho	-0.6072***	0.0869	-6.984	0.6949***	0.0723	9.602	-0.6166***	0.0905	-6.808

Source: Field Survey, Inkoom (2019)

For an unbiased and efficient estimation, the Heckit endogenous treatment effect model assumes that the degree of correlation (ρ or rho) between the two-error term from the selection equation and outcome equation is non-zero. As such, a test of $\rho = 0$ against $\rho \neq 0$ was carried out to evaluate whether the use of the Heckit endogenous treatment effect model for the joint likelihood estimation of the selection equation and outcome equation was appropriate and fits the dataset.

The model summary as shown in Table 7.2 shows that the estimated rho and sigma statistics were significantly different from zero, confirming the superiority of the Heckit endogenous treatment effect model in giving robust and efficient results to the dataset. Again, this indicates that the model estimation was appropriate and that the result is an unbiased estimate of the true treatment effect. Consequently, the model results from the Heckit endogenous treatment effect model can be accepted to be robust and efficient. To test whether there is indeed a direct causal effect of climate smart adaptation on the efficiency of production (farm-level productivity) as suggested by the Heckit treatment effect model, attention was given to the rho estimate. The model summary as presented in Table 7.2 confirms the appropriateness and explanatory power of the Heckit treatment effect model for the analysis of the hypothesised causal effect relationship illustrated in the conceptual framework (*see, Figure 2.2*). The highly and statistically significant coefficient estimates of Rho (0.61, 0.69 and 0.61) suggests that the direct causal effect of the adoption of CSA strategies on the efficiency of production does exist at a 1 percent significant level. This, therefore, confirms the presence of self-selectivity and endogeneity bias problems in the dataset. Accordingly, the study failed to accept the null hypothesis (i.e., $\rho(H_0\!: \rho = 0)$—"*Adoption of CSA practices does not significantly influence the efficiency of production* (*i.e., technical, allocative, and economic*) *among farmers*") in favour of the alternative hypothesis that (i.e., ρ $[(H_1\!: \rho \neq 0)$—"*Adoption of CSA practices significantly influence the efficiency of production (i.e., technical, allocative, and economic) among farmers*").

From the results, as portrayed in Table 7.2 it was manifest that there is an endogenous treatment effect relationship between climate smart adaptation and efficiency of production (i.e., an indicator of productivity growth) among cocoa farmers. Again, the estimated coefficients in the selection equation show that, except for sex, the predicted probability of all the other predictor variables were significant in explaining selection into treatment (i.e., above-average adaptation—adopting a higher level of CSA practices in the presence of climate change) in all three modelling situations. For instance, the result indicates that the probability of self-selecting into treatment is positively influenced by the conditional variables access to extension service, perceived impact of climate change and awareness of available CSA strategies. The estimated positive coefficient of frequency of extension contact as an indicator variable for access to extension means that increases in the frequency of extension contact positively influencing the likelihood of a farmer adopting more CSA measures as adaptation responses to climate change and as means of enhancing the efficiency of production. The observed positive effect of improved extension service delivery on a higher likelihood of improved adoption of CSA technologies confirms other study findings (Issahaku & Abdulai, 2020; Wekesa *et al.*, 2018; Etwire *et al.*, 2013). Furthermore, the estimated positive coefficient of perceived impact of climate change suggests that as the perceived impacts of climate change on productivity increase, the likelihood of farmers to self-select into treatment also increases.

In addition, the results show that the estimated coefficient of farmers awareness of CSA strategies was positive, suggesting that as farmers become more aware of the available CSA strategies, the greater the likelihood to self-select into treatment. This observed relationship between farmers awareness of climate smart adaptation strategies and the decision to adopt is consistent with what other studies have posited (Denkyirah *et al*., 2017; Wiah & Twumasi-Ankrah, 2017; Ehiakpor *et al*., 2016). The result further revealed that the predicted probability of age was estimated to be positive and this suggests that older farmers are more likely to self-select into treatment. Again, the estimated coefficient of education was positive, suggesting that farmers who had a higher level of formal education are more likely to self-select into treatment. The results as portrayed in Table 7.2 also revealed that the estimated coefficient of farming experience was positive and this suggests that farmers with more years in cocoa farming are more likely to self-select into treatment. The statistically significant influence of the predictor variables in the selection equation justifies that to positively stimulate farmers to adopt more CSA technologies, the importance of age, education, frequency of extension contact, climate change impact and awareness of CSA strategies cannot be overlooked. This is because of their consequential effect in complementing the adoption of CSA technologies to impact farm-level efficiency (productivity growth) and subsequently food security of farmers. The significant influences of age, education and farming experience as observed from this study lend empirical credence to other studies' findings on the influence of socio-economic characteristics on climate smart adaptation behaviour among farmers (Akrofi-Atitianti *et al*., 2018; Denkyirah *et al*., 2017; Acquah *et al*., 2017; Selase *et al*., 2017).

Having established the factors that significantly explain selection into treatment, the potential impact of the treatment variable on the outcome variable was then estimated and the results are contained in the three outcome equations presented in Table 7.2. The result as contained in Table 7.2 shows that the treatment variable has a significant direct causal effect on both technical, allocative, and economic efficiencies, conditional on climate change awareness (indicated by use of CSA strategies and risk perception towards CSA strategies) and access to extension service (indicated by access to quality extension service and frequency of extension service). The outcome results indicate that an improved adoption rate of CSA strategies among farmers will impact farm-level productivity growth significantly. Hence, as the adoption of CSA strategies increases, the farm-level efficiency also increases. The estimated positive coefficient of the treatment variable with respect to the three efficiency components indicates that farmers who adopt more CSA strategies in the face of the increasing trend of climate change are more likely to be efficient than their counterparts. Particularly, the estimated treatment effect coefficients of 0.4146, 0.4882 and 0.4838 imply that with an above-average climate smart adaptation, farmers stand the chance of increasing their technical efficiency by 41 percent, allocative efficiency by 49 percent and economic efficiency by 48 percent. Benchmarking the estimated coefficient of the treatment variable to the average count of CSA measures show that above-average adapters are about

31percent [i.e., (0.4146(6/8)) *100] technically more efficient than their counterparts, 37 percent [i.e., (0.4882 (6/8)) *100] allocatively more efficient than their counterparts, and 36 percent [i.e., (0.4838 (6/8)) *100] economically more efficient than their counterparts. This in effect means that if appropriate climate action policy mechanisms are put in place to encourage farmers to adopt more CSA strategies, it will simulate the propensity of increasing farm-level productivity growth, all other things being equal. With reference to the literature, the observed effect of improved adoption of CSA technologies on improvement on farm-level efficiency confirms empirical findings of other studies (Besseah & Kim, 2014; Ogundari, 2013).

Furthermore, the statistically significant causal effect of the adoption of CSA technologies on economic efficiency, technical efficiency and allocative efficiency as established in this study underscores the important role of mainstreaming of climate smart adaptation strategies coupled with the efficiency of production in addressing the livelihood security impact of the persistent low farm-level productivity and the adverse consequence of climate change among cocoa farmers in Ghana. These results, therefore, provide empirical evidence for an economic rationale for policy interventions to concentrate on increasing education on the need for cocoa farmers to adopt more CSA technologies and ensure a higher level of farm-level efficiency of production. However, following the sequential framework under the transitivity rationale, the efficient actualisation of the potential outcome impact of the adoption of CSA strategies on the efficiency of production is only possible should there be an improvement in quality of extension service and climate change awareness. This is supported by the fact that the estimated coefficient of all the conditional variables (risk perception towards CSA strategies, access to quality extension and frequency of extension contact) were noted to be significant and having the expected signs. For instance, the coefficient estimates of CSA risk perception as expected was negative with all three efficiency measures. This suggests that as perceived riskiness in investing in CSA strategies increases, the propensity for farmers to achieve a higher level of technical and economic efficiencies decreases by a margin of 0.1387 and 0.1298. This could be attributed to the potential decrease in the adoption of CSA that is associated with higher risk perception, which then translates into the potential decrease in the farm-level efficiency of farmers.

In addition, the results show that the estimated coefficient of access to quality extension service and the frequency of extension service were both positive. This indicates that an increase in the frequency of extension contact has the potential of increasing technical efficiency by 0.1099 margin, allocative efficiency by 0.0662 margin and economic efficiency by 0.0913 margin. Furthermore, the result indicates that a marginal improvement in the quality of extension enhances farmers technical efficiency by 0.0300 margin, allocative efficiency by 0.0492 margin and economic efficiency by 0.0258 margin. This means that farmers who experience a higher frequency of extension contact coupled with a higher quality of extension service have the propensity of being more efficient than their counterparts. This observation of the effect of access to frequent extension contact supports the assertion made by other studies (Pratama *et al*., 2019; Inkoom & Micah, 2017). One reason that can account for the study finding may be attributed to the timeliness and quality of information delivery, technical advice, and training. Another reason that could account for this is the effective dissemination of technological innovations to farmers by cocoa extension service providers. Consequently, increasing extension contact and provision of quality extension service will potentially lead to the reduction of farm-level inefficiency, and thereby generate higher productivity growth among cocoa farmers.

Furthermore, to investigate the key socioeconomic determinants of efficiency of production (technical, allocative, and economic) some farmer-specific variables were included in the outcome equation of the Heckit treatment effect model. The model results as presented in Table 7.2 show that except for sex and FBO membership, the estimated coefficients of the other farmer-specific variables were significant with respect to the three efficiency components. This means that the observed variability in technical efficiency, allocative efficiency and economic efficiency among farmers is significantly explained by socioeconomic variables such as age, education, farming experience, farm size and access to credit facilities. This observation from the study result attests to what other empirical findings on the effects of these variables on the farm-level efficiencies among farmers (Danso-Abbeam & Baiyegunhi *et al*., 2020; Pratama *et al*., 2019; Fadzim *et al*., 2017; Nicodeme & Suqun, 2017; Abawiera & Dadson, 2016; Onumah *et al*., 2013). The estimated negative coefficient of age with respect to the three efficiency components implies that older farmers were technically, allocatively and economically less efficient in farming. This means that as farmers age in years, their ability to achieve maximum output from minimal input combination at the least cost possible given the existing technology diminishes; causing a significant inefficiency effect.

Again, the estimated positive coefficient of education suggests that having an additional year of education enhance farmers' ability to be technically, allocatively and economically efficient in production. This could be attributed to the fact that education presents opportunities to farmers to improve upon their intellectual and cognitive abilities; thereby giving them an added ability to achieve maximum output from minimal input combination at the least cost possible. Furthermore, the estimated positive coefficient of farming with respect to all three efficiency components, suggests as farming experience increases, the technical, allocative, and economic efficiencies of farmers also increase significantly. This means that farmers with more years of farming experience are often more efficient in production than their counterparts. This can be attributed to the fact that with experiential learning, farmers are able to learn and unlearn to improve upon their production decision making efficiently and a better assertiveness of new technologies. This consequently helps them avoid repeated mistakes and errors in their ability to produce maximum output from minimal input combination at the least cost possible given the existing technology.

Additionally, the estimated coefficient of farm size shows that total land size under cultivation had a positive effect on technical efficiency and economic efficiency but a negative effect on allocative efficiency. This suggests that farmers with large farm sizes were able to take better advantage of the economy of scale effect to be technically and economically efficient in production. Accordingly, with a better economy of scale, farmers can optimise their ability to produce maximum output with minimal input combination at the least cost possible, given the existing technology. Alternatively, it can be said that farmers with a better economy of scale can reduce their technical, and economic inefficiencies effect in production. The negative relationship observed between farm size and allocative efficiency suggests that increases in farm size result in a possible decrease in allocative efficiency. The relationship between farm size and productivity and/or efficiency has been widely debated in the literature for decades and several reasons have been assigned. One of these reasons is the heterogeneous biochemical and physical nature of the land. This may or may not contribute positively to productivity. For instance, the physical nature of the land, such as soil types and contours affect farm operations such as land cultivation, weeding among others. This coupled with the labour-intensive nature of cocoa production activities and other input allocations would explain why land size tends to lower allocative efficiency in cocoa production.

Finally, it was evident from the study result as presented in Table 7.2 that, access to credit showed a negative effect with allocative efficiency in cocoa production. Ordinarily, access to credit is an important factor that is expected to improve farmers' liquidity for timely input acquisition, as well as facilitates the willingness to adopt technological innovation. As such, it was expected that access to credit would have a positive effect on farm-level efficiency and reduce inefficiency. The observed negative effect of credits implies that farmers who did not have access to credit were rather more efficient than their counterparts who had access to credit facilities. This could probably be attributed to the general phenomenon of credit funds being diverted to non-farm related activity. This affects the timely acquisition of farm inputs and technological innovation, which consequently constraint farmers' ability to achieve maximum output from minimal input combinations at the least cost possible.

Furthermore, from the counterfactual argument, the significant positive rho estimates suggest that farmers stand the benefit of achieving a higher level of improved efficiency in production (i.e., higher productivity growth) in the face of climate change should they adopt more CSA strategies. On the other hand, a significant negative rho estimate implies that farmers stand the risk of experiencing low efficiency in production (i.e., low productivity growth) in the face of climate change should they adopt fewer CSA strategies. The realisation of the positive counterfactual is however dependent on the quality of extension service received by farmers. With this, it can be concluded that the improved adoption of CSA strategies coupled with improved quality of extension service does have implications for farm-level efficiency improvement (i.e., farm-level productivity growth). Having established the presence of endogenous treatment effect relationship between the selection equation and the outcome equation, and in following the transitivity, the study proceeded to extend the argument to test the causal link between improved efficiency of production and household food security in sequential order as hypothesised in the conceptual framework (*see Figure 2.2*). The results of which are discussed in Section 7.4 below.

7.4 Heckit Treatment Effect Model Results on the Causal Effect of Economic Efficiency, Technical Efficiency, and Allocative Efficiency on Food Security among Cocoa Farmers

Having demonstrated that the connect between improvement in extension service quality and mainstreaming of climate smart adaptation strategies in cocoa production do have a sequential link implication for improving farm-level efficiency of production; the study went on to estimate the impact of the efficiency of production on household food security. This was aimed to ascertain the collective impact of improved extension service quality, the improved adoption rate of CSA strategies and improved efficiency of production on household food security as demonstrated in the conceptual framework (*see, Figure 2.2*). The implication of this will then give empirical supports to the collective approach to addressing the problem of the livelihood security impact of persistent low farm-level productivity and the adverse consequence of climate change effect on cocoa farmers (*see, Figure 1.1*).

Generally, it is expected that increasing productivity potentially leads to livelihood security improvement of farming households in terms of farm income and household food security situation. However, from the economic theory of production, achieving higher productivity growth is dependent on significant increases in farm-level efficiency of production and technological advancement (i.e., availability and adoption of new technologies). Again, the World Bank definition of agricultural extension indicates that access to quality extension service is critical for stimulating higher adoption of technologies, higher efficiency of production and consequently better food security situation. Thus, conditional on farmers' awareness of the occurrence of climate change (reflected in the use of CSA practices) and access to extension contact (reflected in the quality of extension service), the Heckit treatment effect model was estimated to evaluate the potential and direct causal effect of economic, technical, and allocative efficiencies on household food security status among farmers. The model results are presented in Tables 7.3 to 7.5 and each contains results on the selection equation which describes the factors that influence the likelihood that a farmer will self-select into treatment (i.e., above-average efficiency score—achieve a higher level of efficiency of production or otherwise) and the outcome equation which measures how much household food security condition of farmers will rise or fall with respect to a farmer self-selecting into treatment (i.e., above-average efficiency score).

Following the binomial distribution theorem or the bivariate normality, the study based on the average farm-level efficiency score to group farmers into above-average efficiency score and below-average efficiency score as an indicator of treatment or otherwise (i.e., treatment variable). Accordingly, the study assigned farmers with above-average efficiency scores to be the treatment group as they exhibited a high level of farm-level efficiency and those with below-average efficiency scores to be the control group as they exhibit a low farm-level efficiency. The treatment group were assigned a code of 1 and the control group, a code of 0. The analysis was done at three levels by predicting the treatment effect of technical efficiency, allocative efficiency, and economic efficiency on the four household food security indicators as well as the composite multidimensional food security index (MHFS index). Consequently, five Heckit treatment effect model results were reported in each of the tables. Table 7.3 contains results on the treatment effect of technical efficiency on all household food security indicators. Table 7.4 contains results on the treatment effect of allocative efficiency on all household food security indicators. Table 7.5 contains results on the treatment effect of economic efficiency on all household food security indicators.

To validate the robustness and efficiency of the model estimates, a test of the model fitness was carried out. Theoretically, the test statistic that is used to validate the superiority of the Heckit endogenous treatment effect model over the traditional two-stage regression model is the rho (ρ) estimate. For an unbiased and efficient estimation, the Heckit endogenous treatment effect model assumes that the degree of correlation (ρ, or rho) between the two-error term from the selection equation and outcome equation is non-zero. As such, a test of $\rho = 0$ against $\rho \neq 0$ was carried out to evaluate whether the use of the Heckit endogenous treatment effect model for the joint likelihood estimation of the selection equation and outcome equation was appropriate and fit the dataset. The model summary as shown in Tables 7.3 to 7.5 shows that the estimated rho and sigma statistics were significantly different from zero, confirming the superiority of the Heckit endogenous treatment effect model in giving robust and efficient results to the dataset. Again, this indicates that the model estimation was appropriate and that the result is an unbiased estimate of the true treatment effect. Consequently, the model results from the Heckit endogenous treatment effect model can be accepted to be robust and efficient.

To test whether the estimated treatment effect results of improved technical, allocative, and economic efficiencies on food security as presented in Tables 7.3, 7.4 and 7.5 supports the claim of a direct causal effect of improved efficiency of production on food security as suggested argued in the conceptual framework (*see, Figure 2.2*). The statistically significant coefficient estimates of Rho (0.96, 0.97, 0.64, 0.88, and 0.55 for technical efficiency effect; 0.23, 0.70, 0.34, 0.91, and 0.19 for allocative efficiency effect; and 0.95, 0.97, 0.38, 0.87, and 0.55 for economic efficiency effect) as reported in Tables 7.3, 7.4 and 7.5 affirm that, the direct causal effect of improved efficiency of production on food security does exist at 1 percent significant level. Accordingly, the study failed to accept the null hypothesis (i.e., $\rho[H_0: \rho = 0]$—*"efficiency of production ((technical, allocative, and economic) does not significantly influence the food security status among farmers"*) in favour of the alternative hypothesis (i.e., $\rho[:\rho \neq 0]$—*"efficiency of production (technical, allocative, and economic) significantly influences the food security status among farmers"*).

Treatment Effect of Improved Technical Efficiency on Household Food Security

Here the treatment variable was indicated by the technical efficiency score. From Table 7.3, the selection equation shows that except for sex, all the predictor variables included in the model to explain the likelihood of a farmer self-selecting into treatment (i.e., achieving above-average technical efficiency score—achieving a higher level of technical efficiency) were found to be significant. For instance, under the food availability and food accessibility models, age was estimated to be negative, suggesting that older farmers were less likely to self-select into treatment. Furthermore, from all five model results, education had a positive coefficient estimate, and this suggests that receiving a higher level of education positively impacts the likelihood of farmers self-selecting into treatment.

Again, the estimated positive coefficient of farming experience under the food availability, food utilisation, food stability, and composite MHFS index model, suggests that highly experienced farmers were more likely to self-select into treatment. The results as portrayed in Table 7.3 further show that the estimated coefficient of adoption of CSA strategies as a conditional factor under all five models was positive. This suggests that adopting more CSA strategies, positively enhances the likelihood of farmers self-selecting into treatment. Again, the coefficient of access to quality extension service as a conditional factor was estimated to be positive under all five models.

Table 7.3: Heckit Treatment Effect Model Results on the Causal Effect of Technical Efficiency (TE) on Household Food Security

Variable	**Household Food Security Indicators**								**MFHS index (Pooled Data)**	
	Food Availability		**Food Accessibility**		**Food Utilisation**		**Food Stability**			
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
<u>Selection Equation:</u>										
Intercept	-1.2083***	0.3195	-1.2914***	0.3077	-1.0692**	0.3792	-1.1179***	0.3333	-1.1928***	0.3753
Sex	0.0993	0.0975	0.0963	0.0942	0.0172	0.1112	0.0320	0.1030	0.0285	0.1106
Age	-0.0112**	0.0049	-0.0272***	0.0047	-0.0016	0.0065	-0.0017	0.0052	-0.0015	0.0062
Education	0.0234**	0.0096	0.0472***	0.0090	0.0454***	0.0110	0.0309***	0.0102	0.0491***	0.0110
Farming experience	0.0154***	0.0040	0.0014	0.0035	0.0490***	0.0074	0.0333***	0.0054	0.0511***	0.0071
Frequency of extension contact	0.0196	0.0209	0.0665***	0.0166	0.0130	0.0235	0.0131	0.0216	0.0213	0.0235
Access to quality extension service	0.0380**	0.0140	0.1019***	0.0217	0.1311***	0.0278	0.0486**	0.0172	0.0854**	0.0288
Adoption of CSA technologies	0.4012***	0.0263	0.0508**	0.0249	0.0699**	0.0301	0.0607*	0.0275	0.0580*	0.0309
<u>Outcome Equation:</u>										
Intercept	1.7236***	0.0680	1.2525***	0.1161	0.2695***	0.0239	1.5864***	0.0875	-2.4781***	0.1976
Treatment variable (TE)	0.3098**	0.0177	0.7995***	0.0297	0.4038*	0.2245	0.4191**	0.0296	0.5802***	0.1884
Access to quality extension service	0.0604***	0.0046	0.0605***	0.0079	0.0047***	0.0015	0.0325***	0.0071	0.0707***	0.0129
Adoption of CSA technologies	0.0168***	0.0056	0.0298***	0.0096	0.0077***	0.0019	0.0480*	0.0272	0.0273*	0.0158
Sex	0.0431**	0.0214	0.0488	0.0367	0.0037	0.0071	0.0480*	0.0272	0.1863***	0.0596
Age	-0.0032**	0.0009	-0.0117***	0.0016	-0.0005	0.0004	-0.0068	0.0130	-0.0065*	0.0033
Education	0.0014	0.0020	0.0203***	0.0035	0.0045	0.0075	0.0020	0.0026	0.0234***	0.0061
Household size	-0.0076**	0.0029	-0.0208***	0.0046	-0.0004	0.0017	-0.0251***	0.0046	-0.0422***	0.0129
Off farm economic engagement	0.0023	0.0127	0.0035	0.0190	0.0032	0.0068	0.0153	0.0187	0.1827***	0.0515
Farm income	0.0003*	0.0002	0.0004	0.0003	0.0016	0.0011	0.0047	0.0032	0.0006	0.0008
Model summary										
Sigma	0.2591***	0.0089	0.4445***	0.0158	0.0858***	0.0023	0.3287***	0.0123	0.7058***	0.0338
Rho	0.9610***	0.0091	-0.9725***	0.0081	-0.6449***	0.0729	0.8836***	0.0214	-0.5531	0.1117

Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

Source: Field survey, Inkoom (2019)

This suggests receiving a higher quality of extension service positively enhances the likelihood of farmers self-selecting into treatment. Additionally, the coefficient frequency of extension contact as access to extension conditional factor was estimated to be positive under the food accessibility model. This suggests that increases in the frequency of extension contact increase the likelihood of farmers self-selecting into treatment.

Having established the factors that significantly explain selectivity into treatment, the treatment effect of technical efficiency was then predicted on the food security indicators (i.e., food availability, food accessibility, food utilisation, food stability and the composite MHFS index). The results of this are shown in the outcome equation as presented in Table 7.3. From the table, it was observed that the estimated coefficient of the treatment variable (technical efficiency) was positive and significant under all five models. The results show that achieving a higher technical efficiency level (i.e., above-average technical efficiency score) significantly enhances the likelihood and ability of farmers to sustainably raise their household availability by 31 percent, household food accessibility by 79 percent, household food utilisation by 40 percent, household food stability by 42 percent and consequently their household food security status by 58 percent. Benchmarking the estimated coefficient of the treatment variable to the average farm-level technical efficiency show that farmers with an above-average efficiency score are about 21 percent [i.e., (0.3098(0.67)) *100] more secured with respect to food availability than their counterparts, 53 percent [i.e., (0.7995(0.67)) *100] more secured with respect to food accessibility than their counterparts, 27 percent [i.e., (0.4038(0.67)) *100] more secured with respect to food utilisation than their counterparts, 28 percent [i.e., (0.4191(0.67)) *100] more secured with respect to food stability than their counterparts, and for that matter 38 percent [i.e., (0.5802(0.67)) *100] more food secured than their counterparts. This by implication suggests that improvement in technical efficiency of farmers can stimulate their ability to ensure sufficient and stable food supply; guaranteeing physical and economic access to quality and nutritious food at all times. This could be attributed to the fact that improved technical efficiency raises the productivity of farmers which then gives them a higher farm income leverage and consequently their ability to attain sustainable food security.

The predicted positive and significant impact of technical efficiency on food security was collaborated by the key conditional variables, access to quality extension service and adoption of CSA technologies. The results show that improvement in extension service quality and adoption of CSA strategies significantly raise farmers ability to sustainably achieve better household food availability, accessibility, utilisation, stability and for that matter household food security status. This finding confirms that to significantly address the livelihood security impact of the persistent low farm-level productivity and adverse consequence of climate change on cocoa farmers, a comprehensive policy that encapsulates quality extension service, mainstreaming of CSA and efficiency of production is critical.

Treatment Effect of Improved Allocative Efficiency on Household Food Security

Here the treatment variable was indicated by the allocative efficiency score.

Table 7.4: Heckit Treatment Effect Model Results on the Causal Effect of Allocative Efficiency (AE) on Household Food Security

Variable	Household Food Security Indicators								MHFS index (Pooled Data)	
	Food Availability		Food Accessibility		Food Utilisation		Food Stability			
	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE	Coeff.	SE
Selection Equation:										
Intercept	1.7835***	0.4388	1.7708***	0.4400	1.6900***	0.4340	0.9222**	0.3441	1.7343***	0.4378
Sex	0.3465**	0.1314	0.3315**	0.1305	0.3478**	0.1306	0.3515***	0.1075	0.3333**	0.1309
Age	-0.0008	0.0074	-0.0011	0.0073	-0.0003	0.0072	-0.0118**	0.0053	-0.0015	0.0073
Education	0.0895	0.0123	0.0904***	0.0123	0.0911***	0.0123	0.0602***	0.0103	0.0904***	0.0124
Farming experience	0.0821	0.0108	0.0823***	0.0107	0.0807***	0.0105	0.0272***	0.0070	0.0830***	0.0107
Frequency of extension contact	0.1345***	0.0278	0.1354***	0.0298	0.1204***	0.0273	0.0298*	0.0176	0.1197***	0.0291
Access to quality extension service	0.2669***	0.0354	0.2516***	0.0346	0.2618***	0.0341	0.1449**	0.0253	0.2694***	0.0357
Adoption of CSA technologies	0.0925**	0.0332	0.1065***	0.0336	0.1003***	0.0325	0.1233***	0.0275	0.0956	0.0309
Outcome Equation:										
Intercept	8.0031***	0.3517	3.9512***	0.2761	0.2181***	0.0260	1.5960***	0.0766	-2.9791***	0.1841
Treatment variable (AE)	0.1788***	0.0238	0.5189**	0.1818	0.2135*	0.0075	0.1457***	0.0234	0.7155***	0.1293
Access to quality extension service	0.0414*	0.0235	0.1505***	0.0201	0.0057***	0.0015	0.0308***	0.0052	0.0361**	0.0136
Adoption of CSA technologies	0.1571***	0.0270	0.0759***	0.0211	0.0069***	0.0019	0.0287***	0.0062	0.0603***	0.0140
Sex	0.2206**	0.1011	0.1857**	0.0794	0.0035	0.0072	0.0605**	0.0237	0.1396**	0.0525
Age	-0.0032	0.0052	-0.0102**	0.0041	-0.0023	0.0035	-0.0048***	0.0013	-0.0059**	0.0027
Education	0.0304**	0.0108	0.0286***	0.0085	0.0097	0.0697	0.0111***	0.0023	0.0171**	0.0057
Household size	-0.0089	0.0237	-0.0583***	0.0188	-0.0035	0.0169	-0.0217***	0.0041	-0.0363**	0.0123
Off farm economic engagement	0.1376	0.0979	0.1769**	0.0776	0.0109	0.0069	0.0120	0.0165	0.0155	0.0508
Farm income	0.0029*	0.0016	0.0017	0.0012	0.0197*	0.0115	0.0047	0.0276	0.0005	0.0008
Model summary										
Sigma	1.1939***	0.0343	0.9384***	0.0249	0.0864***	0.0023	0.2864***	0.0093	0.6185***	0.0174
Rho	0.2337***	0.1180	-0.7059***	0.1168	0.3379***	0.0585	-0.9197***	0.0153	-0.1901***	0.0127
Significance codes: '***' 0.01 '**' 0.05 '*' 0.1										

Source: Field survey, Inkoom (2019)

From Table 7.4, the selection equation shows that all the predictor variables included in the model to explain the likelihood of a farmer self-selecting into treatment (i.e., above-average allocative efficiency score—achieving a higher level of allocative efficiency) were found to be significant. For instance, the estimated coefficient of sex was noted to be positive, indicating that male farmers are more likely to self-select into treatment. Again, under the food availability and food accessibility models, age was estimated to be negative, suggesting that older farmers are less likely to self-select into treatment. Furthermore, from all five model results, education had a positive coefficient estimate, and this suggests that receiving a higher level of education positively impacts the likelihood of farmers self-selecting into treatment.

In addition, the estimated positive coefficient of farming experience under the food availability, food utilisation, food stability, and composite MHFS index model; suggests that highly experienced farmers were more likely to self-select into treatment. Again, the coefficient of access to quality extension service as a conditional factor was estimated to be positive under all five models. This suggests receiving a higher quality of extension service positively enhances the likelihood of farmers self-selecting into treatment. Additionally, the coefficient frequency of extension contact as access to extension conditional factor was estimated to be positive under the food accessibility model. This suggests that increases in the frequency of extension contact increase the likelihood of farmers self-selecting into treatment.

Having determined the factors that significantly explain selectivity into treatment (i.e., achieving a higher level of allocative efficiency), the treatment effect of allocative efficiency was then predicted on the food security indicators (i.e., food availability, food accessibility, food utilisation, food stability and the composite MHFS index). The results of this are shown in the outcome equation as presented in Table 7.4. From Table 7.4 it was noted that the estimated treatment variable coefficients (allocative efficiency) under all five models were positive and significant. The results show that achieving a higher allocative efficiency level significantly enhances the likelihood and ability of farmers to sustainably raise their household food availability by 17 percent, household food accessibility by 51 percent, household food utilisation by 21 percent, household food stability by 15 percent and consequently their household food security status by 72 percent. Benchmarking the estimated coefficient of the treatment variable to the average farm-level allocative efficiency show that farmers with an above-average efficiency score are about 12 percent [i.e., (0.1788(0.69)) *100] more secured with respect to food availability than their counterparts, 36 percent [i.e., (0.5189(0.69)) *100] more secured with respect to food accessibility than their counterparts, 15 percent [i.e., (0.2135(0.69)) *100] more secured with respect to food utilisation than their counterparts, 10 percent [i.e., (0.1457(0.69)) *100] more secured with respect to food stability than their counterparts, and for that matter 49 percent [i.e., (0.7155(0.69)) *100] more food secured than their counterparts. This implies that improvement in the allocative efficiency of farmers can stimulate their ability to ensure sufficient and stable food supply; guaranteeing physical and economic access to quality and nutritious food at all times. This may be attributed to the fact that allocative efficiency raises the productivity at the minimum cost possible of farmers which then gives them a higher farm income leverage and consequently their ability to attain sustainable food security.

The predicted positive and significant impact of allocative efficiency on food security was collaborated by the key conditional variables, access to quality extension service and adoption of CSA technologies. The results show that improvement in extension service quality and adoption of CSA strategies significantly raise farmers' ability to sustainably achieve better household food availability, accessibility, utilisation, stability and for that matter household food security status. This finding stands to confirm that to significantly address the livelihood security impact of the persistent low farm-level productivity and adverse consequence of climate change on cocoa farmers, a comprehensive policy that encapsulates quality extension service, mainstreaming of CSA and efficiency of production is critical.

Treatment Effect of Improved Economic Efficiency on Household Food Security

Here the treatment variable was indicated by the economic efficiency score. From Table 7.5, the selection equation shows that except for sex, all the predictor variables included in the model to explain the likelihood of a farmer self-selecting into treatment (i.e., above-average economic efficiency score—achieve a higher level of economic efficiency) were found to be significant. For instance, under the food availability and food accessibility models, age was estimated to be negative, suggesting that older farmers were less likely to self-select into treatment. Furthermore, from all five model results, education had a positive coefficient estimate, and this suggests that receiving a higher level of education positively impacts the likelihood of farmers self-selecting into treatment.

Table 7.5: Heckit Treatment Effect Model Results on the Causal Effect Of Economic Efficiency on Household Food Security

Variable	**Household Food Security Indicators**								**MHFS index (Pooled data)**	
	Food Availability		**Food Accessibility**		**Food Utilisation**		**Food Stability**			
	Coeff.	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**	**Coeff.**	**SE**
<u>Selection Equation:</u>										
Intercept	-0.7746***	0.3257	-0.9130***	0.3090	-0.4677	0.3824	-0.6128*	0.3374	-0.5436	0.3776
Sex	0.1418	0.0984	0.0587	0.0942	0.0718	0.1117	0.0733	0.1042	0.0857	0.1112
Age	0.0097*	0.0051	-0.0275	0.0048	-0.0012	0.0065	-0.0012	0.0053	-0.0045	0.0062
Education	0.0262***	0.0096	0.0480***	0.0090	0.0469***	0.0109	0.0349***	0.0103	0.0503***	0.0110
Farming experience	0.0183***	0.0045	0.0019	0.0037	0.0556***	0.0076	0.0421***	0.0062	0.0588***	0.0073
Frequency of extension contact	0.0453***	0.0147	0.0654***	0.0166	0.1352***	0.0278	0.0579***	0.0182	0.0957***	0.0273
Access to quality extension service	0.0711***	0.0218	0.1583***	0.0223	0.0870***	0.0242	0.0779***	0.0222	0.0937***	0.0239
Adoption of CSA technologies	0.0472*	0.0267	0.0576**	0.0249	0.0242**	0.0301	0.0553*	0.0277	0.0613*	0.0308
<u>Outcome Equation:</u>										
Intercept	4.1119***	0.1541	0.0166***	0.1166	4.5940***	0.1231	1.6668***	0.0855	-2.5911***	0.1901
Treatment variable (EE)	*0.6654****	*0.0445*	*0.7929****	*0.0299*	*0.2213**	*0.1109*	*0.3936****	*0.0322*	*0.5066****	*0.1547*
Access to quality extension service	0.0308**	0.0105	0.0808***	0.0080	0.0182**	0.0089	0.0691***	0.0058	0.0583***	0.0136
Adoption of CSA technologies	0.0376**	0.0128	0.0318***	0.0097	0.0403***	0.0101	0.0328***	0.0070	0.0272*	0.0156
Sex	0.1079**	0.0487	0.0368	0.0369	0.0140	0.0379	0.0549**	0.0268	0.1939***	0.0589
Age	-0.0068**	0.0022	-0.0118***	0.0017	-0.0024	0.0021	-0.0022	0.0129	-0.0075*	0.0031
Education	0.0032	0.0047	0.0208***	0.0035	0.0025	0.0025	0.0021	0.0025	0.0240***	0.0059
Household size	-0.0168**	0.0069	-0.0206***	0.0047	-0.0008	0.0006	-0.0224***	0.0047	-0.0395**	0.0129
Off farm economic engagement	0.0094	0.0094	0.0119	0.0191	0.0197	0.0360	0.0135	0.0191	0.1858***	0.0514
Farm income	0.0007	0.0004	0.0004	0.0003	0.0015	0.0090	0.0041	0.0032	0.0006	0.0008
Model summary										
Sigma	0.5882***	0.0211	0.4465***	0.0159	0.4529***	0.0120	0.3225***	0.0125	0.7058***	0.0338
Rho	0.9530***	0.0113	-0.9733***	0.0081	-0.3800***	0.1052	0.8659***	0.0262	-0.5531***	0.1117

Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

Source: Field survey, Inkoom (2019)

Again, the estimated positive coefficient of farming experience under the food availability, food utilisation, food stability, and the composite MHFS index model; suggests that highly experienced farmers were more likely to select into treatment.

The results as portrayed in Table 7.5 further show that the estimated coefficient of adoption of CSA strategies as a conditional factor under all five models was positive; suggesting that adopting more CSA strategies, positively enhances the likelihood of farmers self-selecting into treatment. In addition, the coefficient of access to quality extension service as a conditional factor was estimated to be positive under all five models. This suggests that receiving a higher quality of extension service positively enhances the likelihood of farmers self-selecting into treatment. Additionally, the coefficient of frequency of extension contact as a conditional factor was estimated to be positive under the food accessibility model, and this suggests that increases in the frequency of extension contact increase the likelihood of farmers self-selecting into treatment.

Having established the factors that significantly explain selectivity into treatment (i.e., above-average economic efficiency score—achieving a higher level of economic efficiency), the treatment effect of economic efficiency was then predicted on the food security indicators (i.e., food availability, food accessibility, food utilisation, food stability and the composite MHFS index). The results of this are presented in the outcome equation as presented in Table 7.5. As portrayed in the table, it was realised that the estimated coefficient of the treatment variable (economic efficiency) was positive and significant under all five models. The results indicate that achieving a higher level of economic efficiency significantly enhances the likelihood and ability of farmers to sustainably raise their household availability by 67 percent, household food accessibility by 79 percent, household food utilisation by 22 percent, household food stability by 39 percent and consequently their household food security status by 51 percent. Benchmarking the estimated coefficient of the treatment variable to the average farm-level economic efficiency shows that farmers with an above-average efficiency score are about 31 percent [i.e., (0.6654(0.47)) *100] more secured with respect to food availability than their counterparts, 37 percent [i.e., (0.7929(0.47)) *100] more secured with respect to food accessibility than their counterparts, 10 percent [i.e., (0.2213(0.47)) *100] more secured with respect to food utilisation than their counterparts, 18 percent [i.e., (0.3936(0.47)) *100] more secured with respect to food stability than their counterparts, and for that matter 24 percent [i.e., (0.5066(0.47)) *100] more food secured than their counterparts.

This result indicates that improvement in the economic efficiency of farmers can stimulate their ability to ensure sufficient and stable food supply, guaranteeing physical and economic access to quality and nutritious food at all times. This may be attributed to the fact that economic efficiency maximises the productivity and profitability of farmers at the minimum cost possible. This presents higher farm income leverage to farmers and consequently farmers' ability to attain sustainable food security status. The predicted positive and significant impact of allocative efficiency on food security was collaborated by the key conditional variables, access to quality extension service and adoption of CSA technologies. The results revealed that improvement in extension service quality and adoption of CSA strategies significantly raise farmers' ability to sustainably achieve better household food availability, accessibility, utilisation, stability and for that matter household food security status. This finding stands to confirm that to significantly address the livelihood security impact of the persistent low farm-level productivity and adverse consequence of climate change on cocoa farmers, a comprehensive policy that encapsulates quality extension service, mainstreaming of CSA and efficiency of production is critical.

Furthermore, from the counterfactual argument, the significant positive rho estimates suggest that with a higher improvement in the efficiency of production, farmers would experience an enhanced improvement in their food security situation. On the other hand, a negative coefficient suggests that farmers stand the risk of experiencing a higher level of food insecurity should they exhibit a low level of efficiency in production. Achieving the positive counterfactual, however, is subject to farmers having access to an improved quality of extension service and an improved adoption rate of CSA strategies. Upon this, a holistic summary of the food security implication of the sequential causal relationship between improved extension service quality, improved climate smart adaptation and improved efficiency of production as hypothesized in the conceptual framework (see, Figure 2.2) is presented in section 7.5 below.

The observation from the three outcome variables clearly shows that improved farm-level efficiency does have significant implications for food security improvement among farmers. The observations made from this study gives strong empirical support to other study findings on the implication of improved farm-level efficiency on food security situation among farmers (Oyetunde-Usman & Olagunju, 2019; Asfaw, Geta, & Mitiku, 2019; Iheke & Onyendi, 2017; Majumder, Bala, Arshad, Haque, & Hossain, 2016; Oyakhilomen, Daniel, & Zibah, 2015).

Farmer Specific Variables that Significantly Explain Variability in Household Food Security across Tables 7.3, 7.4 and 7.5.

Drawing from Tables 7.3, 7.4 and 7.5, it was observed that the farmer-specific variables that significantly explain the variability in household food security situations across the five models include sex, age, education, household size, off-farm economic engagement and farm income. Among these variables, it was observed that the estimated coefficients of age and household size were negative across all five models as shown in Tables 7.3, 7.4 and 7.5. On the other hand, the estimated coefficients of sex, education, off-farm engagement, and farm income as expected were observed to be positive in Tables 7.3 7.4 and 7.5 across all five models. From Tables 7.3, 7.4 and 7.5 the estimated coefficients of sex were observed to be significant under the food availability, accessibility, stability and the composite MHFS index models. This suggests that male-headed households were more likely to achieve better food security status (especially through food availability, food accessibility and food stability) than female-headed households. This could probably be attributed to the socio-economic and cultural environment that often disadvantage women with respect to equality and equity in accessing socio-economic resources and opportunities.

The result further indicates that the estimated negative coefficients of age were significant under the food availability, accessibility, stability and the composite MHFS index models. This implies that older farmers were more likely to experience food insecurity (especially through food availability, food accessibility and food stability) than their counterparts. Furthermore, the estimated positive coefficient of education was found to be significant under the food availability, accessibility, stability and the composite MHFS index models. This indicates that more educated farmers are more likely to be food secured (especially through food availability, food accessibility and food stability) than their counterparts. This can be attributed to the fact that education provides essential abilities to farmers towards efficient decision making respective to their income allocation and farm business activities. Again, the estimated negative coefficients of household size were found to be significant under the food availability, accessibility, stability and the composite MHFS index models. This intuitively suggests that farmers with bigger household sizes were more likely to experience food insecurity (especially through food availability, food accessibility and food stability). This could be attributed to the limited resource available to feed more hands.

In addition, the results as portrayed in Tables 7.3, 7.4 and 7.5 show that the estimated positive coefficients of off-farm economic engagement were significant under the food accessibility and the composite MHFS index models. This means that farmers who engaged in off-farm economic engagement were more likely to be food secured (especially through food accessibility) than their counterparts. This can be ascribed to the additional income that comes to the households from engagement in off-farm economic activities. It was again noted that the estimated positive coefficients of farm income were significant under the food availability and food utilisation models. This means that increases in farm income as a result of increased productivity growth translates into raising the food security situation of farmers (especially through food availability and food utilisation). The observed significant relationship between sex, age, education, household size, access to credit and off-farm economic activities and household food security of farmers confirms other empirical findings (Owusu, Abdulai, & Abdul-Rahman, 2011; Osei, Aidoo, & Tuffor, 2013; Namaa, 2017; Dei Antwi *et al*., 2018).

7.5 Implication of the Heckit Treatment Effect Model Results for the Conceptual Framework as Hypothesised in the Study

The study hypothesized that there is a sequential causal effect relationship between extension service quality, climate smart adaptation, efficiency of production, and household food security. Thus, following a sequential causal framework under a transitivity rational and counterfactual preposition, the Heckit endogenous treatment effect model was estimated to test the null of food security implication of the nexus between extension service quality, climate smart adaptation, and efficiency of production. The import of the hypothesized sequential causal effect relationship as discussed in the conception framework (*see, Figure 2.2*) was to lend empirical support to the comprehensive approach to solving the problem of "*livelihood security impact of the persistent low farm-level productivity and adverse consequence of climate change effect on cocoa production and farmers*" (*see, Figure 1.1*). As already stated, the conceptual justification for using the Heckit endogenous treatment effect model is premised on Figure 2.2. This premise was anchored on the World Bank definition of agricultural extension service.

According to the World Bank, extension service can be defined as the process that helps farmers become aware of improved technologies and adopt them in order to improve their efficiency, income, and welfare. Now to affirm or disaffirm the conceptual framework, it becomes imperative to relate the Heckit treatment effect model results presented in sections 7.2 to 7.4 to the hypothesized relationship presented in Figure 2.2, which aimed at addressing Figure 1.1. To do this, Figure 2.2 was then linked to the study hypothesises 1 to 3 and the outcome presented in Figure 7.1.

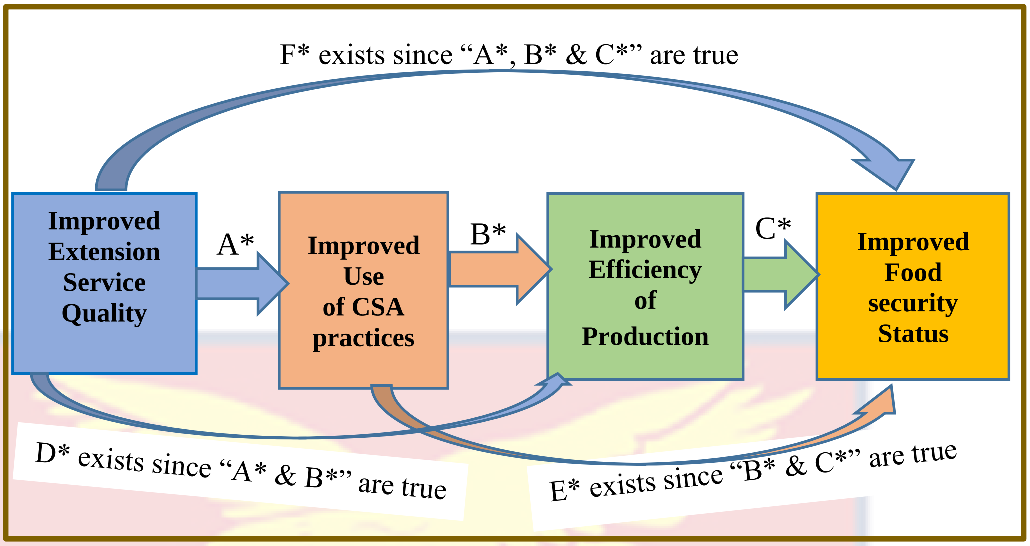


Figure 7.1: Confirmed Path Modelling on the Nexus between Extension Service Quality, Climate Smart Adaptation, Economic Efficiency, and Food Security

Source: Author's Construct, Inkoom (2019)

Hypothesis four of the study tested the causal effect relationship between extension service quality and adoption of CSA technology indicated as "A" in Figure 2.2. From the model test presented in Table 7.1, it was realised that rho was non-zero and statistically significant justifying that the causal link effect "A" truly exists at a 1 percent significance level and this is now represented as "A*" in Figure 7.1. This was confirmed in Table 7.1 in which improved quality of extension service as the treatment variable was estimated to significantly increase the likelihood of farmers adopting more CSA technologies. Furthermore, hypothesis five tested the causal effect relationship between improved adoption of CSA technologies and efficiency of production which is indicated as "B" in Figure 2.2. From the model test presented in Table 7.2, it was realised that rho was non-zero and statistically significant justifying that the causal link relationship "B" truly exists at a 1 percent significance level and this is now represented as "B*" in Figure 7.1. This was confirmed in Table 7.2 in which improved adoption of CSA technologies as a treatment variable was estimated to significantly increase the likelihood of farmers achieving a higher level of efficiency (i.e., higher productivity growth) in the face of climate change. Having proven A* and B* to be true implies that the sequential causal link relationship D* as indicated in Figure 7.1 truly exists. Thus, the consequential implication of A* is that ensuring access to improved extension service quality would positively impact productivity growth working through improved adoption of CSA technologies.

Lastly, hypothesis six evaluated the causal effect relationship between improved efficiency of production (i.e., technical, allocative, and economic) and household food security which is indicated as “C” in Figure 2.2. From the model test presented in Tables7.3, 7.4 and 7.5, it was realised that rho was non-zero and statistically significant, justifying that the causal link relationship “C” in Figure 2.2 truly exists at a 1 percent significance level and this is now represented as “C*” in Figure 7.1. This was confirmed in Tables 7.3, 7.4 and 7.5 in which technical efficiency, allocative efficiency and economic efficiency as a treatment variable were estimated to significantly increase the likelihood of farmers achieving a higher level of household food security in the face of climate change. Having proven A*, B* and C* to be true implies that the sequential causal link relationship E* and F* as indicated in Figure 7.1 truly exists. The consequential inference of Figure 7.1 means that the sequential connects between improved extension service quality, improved adoption of climate smart adaptation technologies, improved efficiency of production and improved food security status do exist. Thus, to holistically address the livelihood security impact of the persistent low-level farm productivity and adverse consequence of climate change effects, any policy concerning the productivity enhancement and climate smart cocoa production programmes must adopt a comprehensive solution framework that incorporates all these key elements (provision of improved quality extension service, mainstreaming of CSA strategies in the cocoa value change and improvement in the farm-level efficiency of production).

7.6 SEM Result: Confirmation of the Implied Relationship in Figure 7.1

To verify if the observed direct and indirect causal inference as demonstrated in Figure 7.1 is not just a chance event, a further confirmatory analysis was done using the structural equation modelling. The empirical application followed the formative approach. The formative approach is recommended when the theoretical path, calls for a composite model that has already been established from a sound theoretical causality framework (Chin, 1998; Bollen & Lennox, 1991; Jarvis, MacKenzie, & Podsakoff, 2003; MacKenzie, Podsakoff, & Jarvis, 2005; Freeze & Raschke, 2007; Roy, Tarafdar, Ragu-Nathan, & Erica, 2012; Kline, 2015). Accordingly, having demonstrated from the Heckit treatment effect model the existence of a sequential causality between extension service quality, climate smart adaptation, efficiency of production and household food security, it became necessary to adopt the formative approach of SEM to confirm the hypothesized direct and indirect relationships between the key construct as illustrated in Figure 7.1. In SEM, it is required that a series of model fitness tests are carried out to validate whether the model appropriately fits the data.

Across the literature, there is growing conflict as to which model fit index is best for SEM (Kline, 2015; Hooper, Coughlan, & Mullen, 2008; Hair *et al.*, 2017). This has led to the development of dozens of fit statistics. As such, the current study followed the commonly reported indices which Kline (2015), Hooper *et al.* (2008) and Hair *et al.* (2017) have suggested researchers can adopt. The result of this is provided in section A of Appendix 3. As shown in section A of Appendix 3, all the model fit indices meet the accepted cut-off required for passing judgement on the good fit of the SEM model. For example, the estimated RMSEA, SRMR and RMR values were found to be less than 0.08 justifying a robust and efficient model fitness (Hooper *et al.*, 2008; Kline, 2015; Hair *et al.*, 2017). Additionally, the goodness of fit statistics of 0.983 being greater than 0.95, and adjusted being greater than 0.90 all affirm that the model appropriately fits the data (Hooper *et al.*, 2008; Kline, 2015; Hair *et al.*, 2017). Also, the comparative fit index and the non-normed fit index all passed. Consequently, it was concluded that the model employed in this study appropriately fits the data. Having established the overall model fitness, the two-stage approach of SEM validation was conducted to assess the fit of the measurement model and the structural model. The test results were accordingly presented in sections B and C of Appendix 3. For example, the 1st eigen value being greater than the 2nd eigen value shows that the measurement model satisfies the Unidimensionality test and that the assumption of construct validity is adequately satisfied. Additionally, the communality values associated with the factor loadings being greater than 0.50 implies that the measurement model satisfies the convergence validity test. Again, the cross-loading values point out that the issue of multicollinearity is absent from the model and that the model satisfies the discriminant validity test. The r-squared and block communality values all being greater than 0.50 suggests a good fit for the structural model.

These test results as presented in Appendix 3 therefore, shows that the SEM results were efficiently and unbiasedly estimated. This then permitted the presentation of the structural model and total effect results in Table 7.6. The path coefficient estimates the direct effect of the endogenous causal variable on the endogenous outcome variable (i.e., the sensitivity of the endogenous outcome variable to changes in the endogenous causal variable). The total effect estimates both the direct and indirect effects of the endogenous causal variable on the endogenous outcome variable. This means that the total effect estimate consists of the direct path coefficient and the indirect path coefficient. Accordingly, the results as presented in Table 7.6 picture the interactive effects between the extension service quality (ESQ), climate smart adaptation (CSA), efficiency of production (i.e., economic efficiency—EE) and household food security status (HFS).

Table 7.6: SEM Results—Confirmation of the Implied Relationship in Figure 7.1

Path coefficient estimate			
Climate smart adaptation:	**Coefficient**	**Standard Error**	**T value**
Extension service quality	0.4170***	0.0339	12.300
Economic efficiency:	**Coefficient**	**Standard Error**	**T value**
Extension service quality	0.4010***	0.0405	9.901
Climate smart adaptation	0. 4090***	0.0405	10.098
Household food security:	**Coefficient**	**Standard Error**	**T value**
Extension service quality	0.3010***	0.0348	8.630
Climate smart adaptation	0.3250***	0.0348	9.340
Economic efficiency	0.5110***	0.0838	6.100

Total effect estimate			
Relationship	**Direct**	**Indirect**	**Total**
ESQ → CSA	0.4171	0.0000	0.4171
ESQ → EE	0.4010	0.0377	0.4387
ESQ → HFS	0.3006	0.1428	0.4434
CSA → EE	0.4090	0.0000	0.4090
CSA → HFS	0.3250	0.0460	0.3710
EE → HFS	0.5110	0.0000	0.5110

Source: Field Survey, Inkoom (2019)

The path coefficient estimates and total effect estimates as portrayed in Table 7.6 were found to be significant, confirming the existence of the observed sequential causal relationship between extension service quality, climate smart adaptation, the efficiency of production and household food security as realised from the Heckit treatment effect model. For instance, the study results as indicated in Table 7.6 show that a marginal improvement in extension service quality will have a sequential impact of about 42 percent improvement in the adoption rate of CSA strategies, 44 percent (i.e., 10 % direct effect and 4% indirect effect) improvement in the efficiency of production and 44 percent (i.e., 30 % direct effect and 14% indirect effect) improvement in household food security among farmers.

Furthermore, the results reveal that a marginal increase in the adaptation rate of CSA strategies will have a sequential impact of about 41 percent improvement in the efficiency of production and about 37 percent (i.e., 32 % direct effect and 5 % indirect effect) improvement in the household food security situation of farmers. Again, study results show that a marginal improvement in the efficiency of production is associated with about 51 percent improvement in the household food security situation of cocoa farmers. These empirical results as realised from the application of the SEM and presented in Table 7.6 strongly support the postulated sequential causal relationship between extension service quality, climate smart adaptation, efficiency of production and household food security as demonstrated from the Heckit treatment effect model. Premised on this, the current study argues that, for the productivity enhancement programme and climate smart cocoa production policy frameworks to be effective in addressing the livelihood security impact of the persistent low farm-level productivity and adverse consequence of climate change in cocoa production, the policy framework must adopt a comprehensive approach that incorporates the interactive effects between the role of extension service quality, mainstreaming of climate smart adaptation strategies and efficiency of production.

Given the significant casual effect relationship observed between extension service quality, climate smart adaptation, economic efficiency, and food security status as confirmed from the empirical analysis, the productivity enhancement programme and climate smart cocoa production system currently being promoted by COCOBOD must factor into the policy framework, these four pillars. The finding of this study also has policy implications for the achievement of about three SDGs [i.e., SDG 1(end poverty); SDG 2 (zero hunger); SDG 12 (responsible consumption and production); and SDG 13 (climate action)].

7.7 Chapter Summary

The chapter presented the discussed results on the connects between extension service quality, climate smart adaptation, the efficiency of production and household food security. The results show that there is a significant sequential causal relationship between extension service quality, climate smart adaptation, the efficiency of production and household food security.

CHAPTER EIGHT

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

This chapter presents a summary of the key findings of the study. In addition, it highlights the major conclusions and recommendations.

8.1 Summary of the Study

This section presents a summary of the study rationale, methodological approach, and empirical findings of this study. In addition, each paragraph emphasizes one objective of the study.

Study Rationale and Methodological Approach

The current study sought to examine the nexus between extension service quality, use of CSA practices, efficiency of production, and the implication for impacting the food security situation among cocoa farmers in Ghana. To address the research objective, the study followed a quantitative research paradigm (positivist approach) and design (descriptive correlational research). A multistage sampling technique was used to collect data from 720 cocoa farmers across the cocoa-growing regions in Ghana. A variety of econometric models including mixed logit model, multivariate probit model, stochastic frontier model, Heckit treatment effect model and structural equation model were employed to analyse the data. A summary of the key findings from the analysis of the data is presented below.

Farmers Perceived Climate Variability and Climate Smart Adaptation Choices

Adaptation to climate change requires knowledge of farmers' perceptions of climate change and variability. The study, therefore, sought to examine whether farmers perceived the occurrence of any significant variability in rainfall and temperature. The study findings show that farmers perceived the occurrence of significant variability in rainfall and temperature over the past decade in the study localities. The extent of the perceived variability was moderate to high according to the perception index score. Again, farmers' perceived impact of climate change and its associated future threat on cocoa production was moderate to high. On the eleven recommended climate smart adaptation strategies that were presented to the farmers, most of the farmers were noted to be aware of them but are currently using eight of them. Particularly, it was observed that most of the sampled farmers were using 5 to 8 of the CSA choices. Furthermore, it was realised that the overall rate of usage was about 53 percent. Again, the risk perception of farmers towards investment in CSA was moderate to high. The multivariate probit results reveal that adopting a mixture of CSA options enhances farmers adaptative capacity and resilience to climate change effect. Again, the multivariate probit result shows that climate variability perception CSA risk perception, climate smart adaptation awareness, perceived impact of climate change, age of farmer, education, FBO membership, years of farming experience, frequency of extension contact and access to credit significantly explain the CSA choices among farmers.

Farmers Perceived Extension Service Quality and Willingness to Pay for Climate Smart Cocoa Extension Service Delivery

It was observed from the results that farmers were not satisfied with the overall extension service quality. They rated the overall service quality to be moderate and that the perceived service quality gap stood about thirty one percent. This was observed to run across the five service quality dimensions. Concerning the determinants of perceived extension service quality, it was observed from the Heckit treatment effect model that the farmer-specific variables that significantly explain variability in the estimated perceived quality index include extension service contact, sex of respondent, age of respondent, educational level of respondent, years of farming experience, FBO membership and access to credit facilities.

On farmers' preference and willingness to pay for the climate smart cocoa extension service scheme, the study findings as obtained from the Discrete Choice Experiment revealed that farmers' utility decreases with price increases, suggesting that farmers will have higher disutility or aversion for a climate smart cocoa extension scheme that is very expensive. In particular, the study results showed that the climate smart cocoa extension service policy should comprise: a monthly subscription fee of GH¢ 10, in-person face-to-face accessibility mode, advanced climate smart cocoa extension service content, a flexible demand-based extension service delivery and above-average service reliability. About their willingness to pay, the study finding showed that farmers are willing to pay GH¢ 2.60 more for an improvement in the service accessibility attribute, GH¢ 7.60 more for an improvement in the service content attribute, GH¢ 7.20 more for an improvement in the service responsiveness attribute, and GH¢ 3.10 more an improvement in the service reliability. Finally, it was observed from the study that extension service quality does have a significant effect in predicting the decision-making behaviour of farmers concerning their willingness to pay for the climate smart cocoa extension service scheme. Furthermore, farmers climate variability perception significantly influenced their willingness to pay. Additionally, socioeconomic variables such as sex, age, education, access to credit and farm income were found to be significant predictors of farmers' willingness to pay.

Characterising Cocoa Farmers Based on the Efficiency of Production and Food Security Estimates

Objectives three and four of this study sought to characterise farmers based on their technical efficiency, allocative efficiency, economic efficiency, and household food security estimates. Furthermore, the farmer-specific variables that significantly explain variabilities in these estimates were investigated. The results of the Cobb-Douglas stochastic production and cost frontier models revealed that farmers exhibited significant levels of technical, allocative, and economic inefficiencies in production. The estimated output elasticities from the stochastic production frontier model revealed that the estimated production function is monotonically increasing for labour, fertiliser, and capital inputs, but is monotonically decreasing for agrochemical/pesticide inputs. Again, it was noted from the production frontier model that except for capital, all the other three input variables (i.e., labour, fertilizer, and agrochemicals) were significant in defining the production function. For the stochastic cost frontier model, the estimated cost elasticities show that the cost function was monotonically non-decreasing for labour, fertilizer, capital, and yield, but for decreasing for agrochemical inputs.

In addition, the estimated coefficients of all the predictor variables in the cost frontier model were significant in defining the observed cost function. The distribution of the farmers based on their estimated efficiency scores across the three efficiency components showed that most of them exhibited a moderate to a high level of farm-level efficiency of production. To understand what accounts for the observed efficiency variability, the study went on to predict the drivers or determinants of technical, allocative, and economic efficiency in cocoa production. From the Heckit treatment effect model result, it was realised that the farmer specific factors that significantly explain variability in the estimated efficiency scores include extension service contact, CSA risk perception, age, education, years of farming experience, land size under cocoa production and access to credit facilities.

Now concerning the household food security estimates, farmers were assessed based on the four-food security dimension (i.e., food availability, food accessibility, food utilisation, and food stability) as opined by FAO (1966). From the results, it was observed that when it comes to household food availability as a food security indicator, farmers on average are marginally food secured. Again, the estimated HFS index associated with household food accessibility as a food security indicator again depicts that farmers on average are marginally food secured. From the household food utilisation food security indicator, the estimated HFS index revealed again the farmers on average are marginally food secured. Furthermore, from the household food stability food security indicator, the estimated HFS index indicated that farmers on average are marginally food secured. This was affirmed by the estimated weighted mean HFS index which showed that farmers on average are indeed marginally food secured. The results further revealed that in analysing household food security, the measurement approach does matter. It was realised that a multidimensional index gives a better representation of the household food insecurity problem. It was again, noted that food stability is the highest contributor to the household food insecurity problems among farmers. Given the observed variability in the household food security situation among farmers, a model was run to investigate the factors that significantly explain the observed variability. From the Heckit treatment effect model results, it was observed that the farmer specific factors that significantly explain household food security status of cocoa farmers include sex of farmers, age, household size, education, credit access, off-farm economic engagement, and farm income.

Connects between Extension Service Quality, Climate Smart Adaptation, Efficiency of Production and Farm Household Food Security

In evaluating the sequential causal relationship between extension service quality, climate smart adaptation, the efficiency of production and household food security, the study employed the Heckit treatment effect model as a counterfactual model and the structural equation modelling as a confirmatory assessment of the findings from the Heckit treatment effect model. The application of the Heckit treatment effect model followed a sequential causal inference framework under a transitivity rationale. The structural equation modelling, on the other hand, followed the formative modelling approach. From the Heckit treatment effect model results, it was observed that there is a significant treatment effect (i.e., causal effect relationship) between extension service quality and the adoption of CSA strategies and this was collaborated by the SEM results. The Heckit treatment effect model results further revealed the existence of a significant causal effect relationship between adoption of CSA strategies and efficiency of production (i.e., productivity growth), and this observed relationship was further confirmed by the SEM result.

Lastly, the Heckit treatment effect model results proved that improvement in the efficiency of production has a significant and direct causal effect on the household food security situation of cocoa farmers, and this was further affirmed by the SEM result. Conclusively, the application of the Heckit treatment effect model and the structural equation modelling affirms that the significant sequential causal relationship between improvement in extension service quality delivery, mainstreaming of climate smart adaptation strategies in cocoa production and improvement in the efficiency of production and household food security is critical for addressing the livelihood security impact of the persistent low farm-level productivity and adverse consequence of climate change effect in cocoa production in Ghana.

8.2 Conclusions

From the analysis and empirical findings of the study, the following conclusions were made:

1. Cocoa farmers have significant knowledge on the occurrence of climate change and variability, and that their climate variability and change perceptions with respect to rainfall and temperature variability as well as perceived impact of climate change, climate smart adaptation awareness and risk perception about climate smart adaptation significantly influenced their climate smart adaptation choices.
2. From the perspective of cocoa farmers, the quality of extension service received was moderate with a significant quality gap and that their service quality perception index significantly influenced their willingness to pay for an improved extension service that is integrated with climate smart adaptation information.
3. There were significant levels of inefficiency effects in cocoa production in the major cocoa growing areas in Ghana. That is, cocoa farmers were not technically, allocatively and economically fully efficient, and that the observed efficiency differentials were significantly explained by factors such as the adoption of CSA, CSA risk perception, access to quality extension service, frequency of extension service, sex, education, years of farming experience, land size under cocoa production and access to credit.
4. The majority of the cocoa farmers in the cocoa-growing areas in Ghana on average were marginally food secured in terms of household food

availability, household food accessibility, household food utilisation and household food stability. It was clear that compared to the unidimensional approach, the multidimensional approach to food security assessment gives a better representation of the household food insecurity problem.

5. It was observed that there is a significant sequential causal treatment effect relationship between improved extension service quality, improve the adoption rate of CSA technologies, improved farm-level efficiencies of production and improved household food security status. Thus, ensuring access to improved quality extension service in the presence of climate change can potentially lead to improved adoption of CSA technologies among cocoa farmers. When this is efficiently actualized, a combined sequential effect of quality extension service and higher adoption of CSA technologies would lead to productivity improvement (indicated by higher efficiency of production) and consequently a better improvement in the household food security situation of cocoa farmers.

8.3 Recommendations

Based on the conclusions drawn from the study, the following recommendations are made:

1. To address the observed service quality gap with respect to the five-service quality dimension (i.e., tangibility, reliability, responsiveness, assurance, and empathy), COCOBOD must take necessary measures to improve upon the appropriateness of both physical, human, and technological resources to deliver accurate and dependable service to farmers. That is, regular training should be given to cocoa extension agents to improve their competencies and skills so as to render efficient

and prompt service delivery to farmers. The material and technological resources needed to deliver efficient resources should be adapt-to-date and readily available at the district cocoa offices. Additionally, to instil high trust and confidence in farmers in relation to the use of the information disseminated to them, a farmer-oriented human relation approach must be adopted by cocoa extension agents under COCOBOD.

2. To generate the likelihood of higher participation of cocoa farmers in a cost-sharing extension service, COCOBOD must develop an extension service package that integrates climate smart adaptation information. In addition, COCOBOD must intensify and prioritised their promotion and education on climate smart adaptation measures to farmers. COCOBOD must direct its attention to climate financing mechanism that increases investment in climate smart adaptation initiatives and innovations.
3. To address the issue of economic, technical, and allocative inefficiencies in cocoa production, COCOBOB should incorporate into its farmer field school the concept of resource use efficiency when training or educating farmers on the best agronomic practices and basic economics of running a farm business. Again, more resources should be channelled by COCOBOD into providing continuous and up-to-date business and economics management practices and information to cocoa farmers both at the farmer level and corporative level through the farmer field school programme, radio programme, and field demonstration programme.
4. To build a more sustainable resilience and adaptive capacity to climate change effect on farm household livelihood security, cocoa farmers must adopt more climate smart adaptation strategies to be able to improve

upon their efficiency of production and consequently their household food security status.

5. Given the established sequential causal treatment effect between improved extension service quality, improved climate smart adaptation technologies adoption, improved efficiency of production and improved food security; COCOBOD going forward in the implementation of the productivity enhancement and climate smart cocoa production initiatives must adopt a holistic and comprehensive framework that centres on the interactive relationship between improved quality extension service delivery, mainstreaming of climate smart adaptation and improved efficiency of production. This will comprehensively help address the effect of the adverse consequence of climate change and the persistent low farm-level productivity on the livelihood security enhancement of cocoa farmers.

8.4 Contribution to Knowledge

The current study followed an integrative modelling approach based on a different theoretical and conceptual framework to analyse emerging issues such as quality of extension service, willingness to pay for improved extension service, climate change and climate smart adaptation, the efficiency of production and livelihood security (especially, food security situation) in the cocoa farming enterprise. The integrative analytical approach adopted by the current study makes a significant contribution to existing literature that have propounded varieties of solution to address the livelihood security impact of the adverse consequence of climate change and the persistent low farm-level productivity in cocoa production. The study, therefore, fills the knowledge gap in the literature on the complexity of the sequential causal and interactive relationships among the key variables of the study among cocoa farmers in the cocoa-growing regions in Ghana. In practice, the model used in this study could serve as a tool for change agents for addressing the livelihood security impact of the persistent low farm-level productivity and adverse consequences of climate change among farmers.

8.5 Suggestions for Further Studies

Based on the observed findings from this study, it is recommended that the study be replicated to cover the other cocoa regions that were randomly selected against in the study for a more comprehensive evaluation of how the nexus between extension service quality, climate smart adaptation and efficiency of production can impact on the food security status of farmers to help guide appropriate policy initiatives. It is further suggested to other studies to consider the multidimensional food security modelling approach that incorporated the sustainability and urgency dimension of food security. Lastly, given that the current study utilised cross-sectional data, it is recommended for further studies to consider the use of longitudinal (panel) data to accounts for the time dimension or trend analysis of food security and efficiency variability.

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APPENDICES

Appendix 1: Structured Interview Schedule

UNIVERSITY OF CAPE COAST
DEPARTMENT OF AGRICULTURAL ECONOMICS AND EXTENSION
STRUCTURED INTERVIEW SCHEDULE

This exercise is purely for academic work only. All information obtained would only be used for academic purposes and would be treated with the strictest confidence. It is a survey as part of my postgraduate research project.

Name of enumerator……………………………

Questionnaire code…………………. Date of interview: …………….

District Name……………… Community name ……………

PART 1: FARM AND FARMER-SPECIFIC CHARACTERISTICS

1. Sex of respondent: Male [] Female []
2. Age of respondent………………………...
3. Household size of respondent: …………………………………
4. Years of formal education of respondent (years spent in school): …
5. Educational level of respondents: i. No Formal education []
   ii. Primary Education [] iii. Middle level / JHS []
   iv. SHS / O-Level / A-level [] iv. Tertiary Education []
6. Please what is your current marital status? Married [] ii. Not married []
7. Apart from farming, are you engaged in any other economic activities:
   Yes [] No []
8. Are you a member of any farmer-based organisation? Yes [] No []
9. How many years have you been engaged in cocoa farming?……
10. What title do you hold to the land under cultivation?
    i. Own land [] ii. Family land [] iii. Leased []
11. Do you have access to extension service? Yes [] No []
12. If Yes to 11, what is the number of extensions contact per production period…
13. Have you accessed credit (formal or informal) before? Yes [] No []
14. If yes to 13, what are the sources of the credit?
    i. Bank loan [] ii. micro-credit facilities [] iii. Cooperative loan []
    vi. Friends/Relatives [] v. Local money lenders []
15. What source of labour do you use in your cocoa production?
    i. family labour [] ii. Hired labour []

INPUTS AND OUTPUT QUANTITIES (PREVIOUS YEAR COCOA SEASON)

Variable Inputs	Quantity per season	Cost per unit (GHs)	Total cost per season (GHs)
Fertiliser (kg):			

Pesticides (L):			
Herbicides			
insecticides			
fungicides			
Labour for weeding			
Family labour			
Hired Labour			
Labour for harvesting			
Family labour			
Hired Labour			
Labour for fertiliser application			
Family labour			
Hired Labour			
Labour for pesticides application			
Family labour			
Hired Labour			
Land under cultivation		Land size (Arches)	Unit cost
land area under cocoa production			
Output Quantity details for last production season			
Output	Cropping Season	Major (Quantity in bags)	Minor (Quantity in bags)
Yield	2017/2018		
Other capital equipment			
Item	Quantity of items	Unit price of item	
Cutlass			
Knapsack Sprayer			
Mechanical sprayer			
Harvesting sickle knife			

PART 2: KNOWLEDGE OF FARMERS ABOUT CLIMATE CHANGE AND CLIMATE VARIABILITY

16. Please indicate to what extent you have observed significant variability in rainfall patterns over the past 5 years? Use a scale of “1= Insignificant change” to “10=highly significant change”

1	2	3	4	5	6	7	8	9	10

17. Please indicate to what extent you have observed significant variability in temperature over the past 5 years? Use a scale of “1= Insignificant change” to “10=highly significant change”

1	2	3	4	5	6	7	8	9	10

18. How would you describe the onset of rainfall season within the last 5 years compared with the periods when you started farming?
A) Earlier onset [] B) late onset [] C) no observable change []

19. Please indicate if any, what has been the change in the total amount of annual rainfall in this area from when you started farming till now? Use a scale of "1 = large decrease" to "10= large increase"

1	2	3	4	5	6	7	8	9	10

20. Please indicate if any, what has been the change in the number of rainy days during the growing season in this area from when you started farming till now? Use a scale of "1 = large decrease" to "5= large increase"

1	2	3	4	5	6	7	8	9	10

21. Please indicate if any, what has been the change in the spread of rainy days that you have observed during the growing season in this area from when you started farming till now? Use a scale of "1 = More concentrated" to "10 = More spread out"

1	2	3	4	5	6	7	8	9	10

22. Please indicate if any, what has been the change in temperature that you have observed during the growing season in this area from when you started farming till now? Use a scale of "1 = Much colder" to "10 = Much hotter"

1	2	3	4	5	6	7	8	9	10

23. Please indicate to what extent each of the following climatic conditions has impacted on your production or livelihood? Use a scale of "1=very low impact" to "10 = very high impact"

Adverse climatic condition	1	2	3	4	5	6	7	8	9	10
Drought										
Flooding										
Too early onset of rains										
Too last onset of rains										
Erratic rainfall pattern										
Long period of intense heat										

24. Looking into the future indicates the degree to which the following climate condition presents a worrying situation to you. Use a scale of "1=not at all worried" to "10 = extremely worried"

Adverse climatic condition	1	2	3	4	5	6	7	8	9	10
Drought										
Flooding										
Too early onset of rains										
Too last onset of rains										
Erratic rainfall pattern										
Long period of intense heat										

PART 3: CLIMATE-SMART ADAPTATION STRATEGIES

25. Please indicates which of the climate adaptation technology option you do have knowledge about and have used before or currently using in your cocoa production

Adaptation technology	Knowledge about CSA options			Use of CSA option			Score your Risk perception toward investment in CSA		
	Yes	No		Yes	No		Safe	Risky	
Use of Improved variety seeds and seedlings									
Fertiliser application									
Pesticides application									
Plant shade trees									
Mixed cropping (Crop diversification)									
Livestock rearing (non-crop diversification)									
Off-farm income diversification									
Changing the planting date									
Crop insurance									
Irrigation									
Hand Pollination (artificial pollination)									

26. How did you come to know of the adaptation options presented in question 26?

Source	Please tick all those that apply
Agricultural extension agents	
Colleague farmer	
Media (e.g. Radio)	
Researcher	
NGOs	
Friends/relatives	
Others (specify)	

27. Please on a scale of "1=very low" to "10=very high", rate the effectiveness of the various adaptation option as a good coping measure to climate change effect

Adaptation technology	Please tick appropriate									
	1	2	3	4	5	6	7	8	9	10
Use of Improved variety seeds and seedlings										
Fertiliser application										
Pesticides application										
Plant shade trees										
Mixed cropping (Crop diversification)										

Livestock rearing (non-crop diversification)										
Off-farm income diversification										
Changing the planting date										
Crop insurance										
Irrigation										
Artificial Pollination (Hand Pollination)										

PART 4: ELICITATION OF FOOD SECURITY SITUATION OF COCOA FARMERS

Section I: Food Availability and Utilisation Component:
Please indicates which food item is frequently consumed by the household and is readily available to the household

Food items	Food items available over the last 7 days		Food items consumed in the last 24 hours	
	Yes	No	Yes	No
Grains & Cereals				
*Rice				
*Maize				
Root and tubers				
*Yam				
*Cassava				
*Plantain				
*Cocoyam				
Fish and Meat Product				
*fresh fish				
*smoked fish				
*fried fish				
*Poultry meat				
*Animal meat				
*Bushmeat				
Milk and Egg products				
*liquid can milk				
*Milk powder				
*Boiled Egg				
*fried Egg				
*Egg Stew				
Fats and Oil				
*Palm oil				
*Coconut oil				
*Frytol				
Fruits				
*Orange				
*Banana				
*Pineapple				
*Pawpaw				
*Pear				
*Mango				

Vegetables				
*Tomatoes				
*Garden egg				
*Cabbage				
*Carrots				
*Cocoyam leaves				
*onion &garlic				
Nuts and Legumes				
*Beans (e.g. cowpea, soya beans, etc)				
*Groundnuts				
Bakery Products and Beverages				
*Bread				
*Cocoa beverage				
*Coffee beverage				

28. Please rank the major source of food availability (e.g. 1=the top most & 5= the least)

Major source	**Rank**
Domestic production from own farm	
Purchased from market	
Gifts	
Food aid from friends/family	
Food aids from public and private organisations	

SECTION II: FOOD ACCESSIBILITY DIMENSION

29. The table below is supposed to help us assess the extent of household food accessibility over the past 7 days due to lack of food or inadequate money for food

	Response Questions	Tick appropriate
1	In the past 7 days, how often did you worry that your household would not have enough food?	Never [] Rarely [] Sometimes [] Often []
2	In the past 7 days, how often were you or any household member not able to eat the kinds of foods you preferred because of a lack of resources (money)?	Never [] Rarely [] Sometimes [] Often []
3	In the past 7 days, how often were you or any household member have to eat a limited variety of foods due to a lack of resources (money)?	Never [] Rarely [] Sometimes [] Often []
4	In the past 7 days, how often were you or any household member have to eat some foods that you really did not want to eat because of a lack of resources (money) to obtain other types of food	Never [] Rarely [] Sometimes [] Often []
5	In the past 7 days, how often did you or any household member eat less food either in the morning or evening than you felt you needed because there was not enough food?	Never [] Rarely [] Sometimes [] Often []
6	In the past 7 days, how often did you or any other household member have to eat fewer than three meals in a day because there was not enough food?	Never [] Rarely [] Sometimes [] Often []

7	In the past 7 days, how often was there ever no food to eat of any kind in your household because of a lack of resources (money) to get food?	Never [] Rarely [] Sometimes [] Often [ ]
8	In the past 7 days, how often did you or any household member go to sleep at night hungry because there was not enough food?	Never [] Rarely [] Sometimes [] Often []
9	In the past 7 days, how often did you or any household member go a whole day and night without eating anything because there was not enough food?	Never [] Rarely [] Sometimes [] Often []

SECTION III: VULNERABILITY OR STABILITY DIMENSION

30. Please in situations of experiencing frequent food deficit or running out of cash, how does the household manage to get sufficient food for consumption? Please tick where appropriate

Coping strategies adopted in the face of persistent food and budget deficit	Uses		Frequency of use (1=less frequent to 10 = more frequent)									
	Yes	No	1	2	3	4	5	6	7	8	9	10
1. Rely on less preferred food												
2. Rely on less expensive food												
3. Borrow food												
4. Borrow money to buy food												
5. Purchase food on credit												
6. Rely on help from relatives or friend outside household without having to pay back.												
7. Limit your own intake to ensure child gets enough												
8. Limit portions at mealtimes												
9. Reduce number of meals eaten in a day												
10. Skip whole day without eating												

PART 5: ASSESSMENT OF QUALITY OF EXTENSION SERVICE RECEIVED BY FARMERS

Please how would you rate the quality of extension service received from service providers considering their performance (*"1=Very low Performance" to "10=Very High Performance")*

Your Experience	1	2	3	4	5	6	7	8	9	10
Tangibility items										
1. The service provider uses state-of-the-art technology in information dissemination										
2. The service provider employs a participatory learning approach in training farmers										
4. Materials associated with services delivery such as training manuals, Flip Chart, demonstration plots are visually appealing										
5. The operational offices of the service providers are easily accessible										
Reliability items										
6. When the service provider promises to do something by a certain time, it does it										

7. When a customer has a problem, the AEAS shows sincere interest in solving it										
8. The service provider performs it services right the first time										
9. The service providers provides its services at the time as promised										
10. The training and service offered are of good quality and meet my needs										
Responsiveness items										
11. The AEAs give prompt service										
12. The AEAs make information easily obtainable by me										
13. The AEAs are always willing to help me										
14. The AEAs are never too busy to respond to my request										
Assurance items										
15. The behaviour of AEAs instil or inspire confidence in me										
16. AEAs are polite and courteous with me										
17. AEAs are well knowledgeable about emerging issues in cocoa production										
18. I feel safe in discussing my farm problems with the AEAs										
Empathy items										
19. The AEAs give individual attention to farmers										
20. The AEAs understand the specific needs of farmers										
21. Uses convenient operating and meeting hours to discusses issues and train farmers										
22. The extension department and AEAs have farmers' best interest at heart										
23. It is very easy to reach out to AEAs in terms of emergency										

Definition of Quality Dimension

- **Tangibility:** Physical facilities, equipment, and appearance of employees
- **Reliability:** Ability to perform the promised service dependably and accurately
- **Responsiveness**: Willingness to help customers and provide prompt service.
- **Assurance:** Knowledge and courtesy of service providers and their ability to inspire trust and confidence
- **Empathy**: Caring and individualized attention that the service providers give to their customers

PART 6: ELICITING FARMERS PREFERENCE AND WILLINGNESS TO PAY FOR CLIMATE SMART COCOA EXTENSION SERVICE

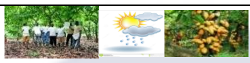
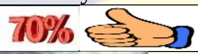
Please you are present with two alternatives to improve extension service, please indicate your choice of extension service alternative you would prefer.

The improved extension service provides a climate smart cocoa extensive services, that cushion you against climate change effect.

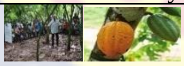
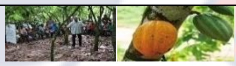
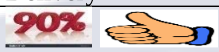
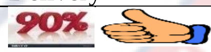
Preamble to product attributes:

- Accessibility—defines the preferred mode of service delivery and access to service
- Content—defines the preferred service content and its perceived relevance and usefulness
- Responsiveness—defines preferred frequency and promptness of service delivery
- Reliability—defines the extent or degree to which the service provided is accurate and dependable
- Price—defines the preferred service charge per month per season
- ACSCES—Advance Climate Smart Cocoa Extension Service
- TCES—Traditional Cocoa Extension Service

Choice card 1—Which extension scheme alternative would you prefer? Tick appropriately

Attributes	**Alternative A** [ ]	**Alternative B** [ ]	**Neither A / B [ ]**
Accessibility	 Virtual accessibility mode	 Virtual accessibility mode	
Content	 ACSCES	 ACSCES	
Responsiveness	Flexible Demand-Based Service Delivery	Flexible Demand-Based Service Delivery	
Reliability			
Price	 GH¢20	 GH¢15	

Choice card 2—Which extension scheme alternative would you prefer? Tick appropriately

Attributes	**Alternative A** [ ]	**Alternative B** [ ]	**Neither A/B** [ ]
Accessibility	 In person face-to-face accessibility mode	 Virtual accessibility mode	
Content	 TCES	 TCES	
Responsiveness	Flexible Demand-Base Service Delivery	Fixed Schedule Service Delivery	
Reliability			
Price	 GH¢20	 GH¢10	

Choice card 3 —Which extension scheme alternative would you prefer? Tick appropriately

Attributes	**Alternative A** [ ]	**Alternative B** [ ]	**Neither A/B** [ ]
Accessibility	 Virtual accessibility mode	 In-person face-to-face accessibility mode	
Content	 ACSCES	 ACSCES	
Responsiveness	Fixed Schedule Service Delivery	Fixed Schedule Service Delivery	
Reliability			
Price	 GH¢20	 GH¢15	

Choice card 4—Which extension scheme alternative would you prefer? Tick appropriately

Attributes	**Alternative A [ ]**	**Alternative B [ ]**	**Neither A/B [ ]**
Accessibility	In personal face-to-face accessibility mode	In personal face-to-face accessibility mode	
Content	TCES	ACSCES	
Responsiveness	Fixed Schedule Service Delivery	Flexible Demand-Base Service Delivery	
Reliability	50%	70%	
Price	GH¢20	GH¢20	

Choice card 5 —Which extension scheme alternative would you prefer? Tick appropriately

Attributes	**Alternative A [ ]**	**Alternative B [ ]**	**Neither A/B [ ]**
Accessibility	In person face-to-face accessibility mode	Virtual accessibility mode	
Content	ACSCES	ACSCES	
Responsiveness	Flexible Demand-Base Service Delivery	Flexible Demand-Base Service Delivery	
Reliability	50%	50%	
Price	GH¢10	GH¢10	

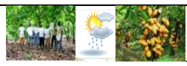
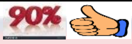
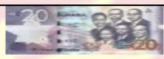
Choice card 6 —Which extension scheme alternative would you prefer? Tick appropriately

Attributes	**Alternative A [ ]**	**Alternative B [ ]**	**Neither A/B [ ]**
Accessibility	In person face-to-face accessibility mode	Virtual accessibility mode	
Content	TCES	ACSCES	
Responsiveness	Fixed Schedule Service Delivery	Fixed Schedule Service Delivery	
Reliability	90%	70%	
Price	GH¢10	GH¢15	

Choice card 7—Which extension scheme alternative would you prefer? Tick appropriately

Attributes	**Alternative A [ ]**	**Alternative B [ ]**	**Neither A/B [ ]**
Accessibility	Virtual accessibility mode	Virtual accessibility mode	
Content	ACSCES	TCES	
Responsiveness	Flexible Demand-Based Service Delivery	Fixed Schedule Service Delivery	
Reliability	50%	70%	
Price	GH¢20	GH¢20	

Choice card 8—Which extension scheme alternative would you prefer? Tick appropriately

Attributes	**Alternative A [ ]**	**Alternative B [ ]**	**Neither A/B [ ]**
Accessibility	 Virtual accessibility mode	 Virtual accessibility mode	
Content	 TCES	 ACSCES	
Responsiveness	Flexible Demand-Base Service Delivery	Fixed Schedule Service Delivery	
Reliability			
Price	 GH¢15	 GH¢20	

Appendix 2: Reliability test of the Data Collection Instrument

Results on Cronbach alpha reliability test of the instrument

Items	**Cronbach alpha estimates**
Perceived impact of climate change	0.71
Perceived future threat of climate change	0.74
Knowledge about CSA options	0.73
Risk attitudes towards investing in CSA options	0.89
Use of CSA options	0.70
Effectiveness of CSA options	0.73
Household food availability	0.76
Household food consumption	0.79
Household food accessibility	0.87
Household food stability or vulnerability	0.89
SERVEPERF (service quality scales)	0.97

Source: Field survey, Inkoom (2019)

Appendix 3: Model Evaluation of SEM: Assessment of the Measurement Model and Latent Model

A) Model fitness indices

Fit indices	**Description**	**Estimated Value**	**Accepted value (cut-off for a good fit)**
Chi-square	Assess overall fit and the discrepancy between the sample and fitted covariance matrices. Sensitive to sample size. H0: The model fits perfectly.	0.984 (p-value)	P value > 0.05
RMSEA	Root Mean Square Error of Approximation A parsimony-adjusted index. A value closer to 0 represents a good fit	0.000	RMSEA< 0.08

SRMR	The Standardized Root Mean Square residual. A value closer to 0 represent a good git	0.029	SRMR < 0.08
RMR	Root Mean Residual. A value closer to 0 means a good fit	0.051	RMR < 0.08
GFI	Goodness of fit. It is the proportion of variance accounted for by the estimated population covariance. A value greater than 0.95 means a good fit.	0.983	GFI ≥ 0.95
AGFI	Adjusted Goodness of fit. A value greater than 0.90 means a good fit	0.978	AGFI ≥ 0.90
CFI	Comparative Fit Index. Compares the fit of a target model to the fit of an independent or null model. A value greater than 0.90 means a good fit.	1.000	CFI ≥ 0.90
NNFI	Non-Normed Fit Index. Indicates the model of interest improves the fit by 95% relative to the null model. A value greater than 0.95 means a good fit.	1.954	NNFI ≥ 0.95

Source: Field survey, Inkoom (2019)

B) Assessment of the measurement model—Unidimensionality

Dimensionality Indices for Reliability test

Latent Construct	Measurement variable	Cronbach alpha	Dillon-Goldstein's rho	1st eigen value	2nd eigen value
Extension service quality	5	NA	NA	3.62	0.069
Climate smart adaptation	8	NA	NA	2.32	0.237
Efficiency of production	3	NA	NA	1.04	0.694
Household food security	4	NA	NA	1.62	0.366

Convergence Validity—Factor Loading

Block	**Indicator Name**	**Weight**	**Loading**	**communality**
Extension Service Quality	Tangibility	0.3469	0.8321	0.6924
	Reliability	0.1503	0.8304	0.6896
	Responsiveness	0.1534	0.8258	0.6819
	Assurance	0.3072	0.8685	0.7543
	Empathy	0.2266	0.8520	0.7259
Economic efficiency	Technical efficiency	0.2751	0.8459	0.7155
	Allocative efficiency	0.9514	0.9615	0.9244
Climate smart adaptation	Improved crop variety	0.2839	0.8686	0.7545
	Optimal fertilise use	0. 4099	0.9445	0.8921
	Optimal pesticide use	0.4326	0.8132	0.6612
	Changing planting dates	0.4029	0.8363	0.6993
	Shade tree management	0.2461	0.7261	0.5272
	Crop diversification	0. 2009	0.8140	0.6626
	Non crop diversification	0.3262	0.7032	0.4944
	Off farm diversification	0.9569	0.8589	0.7380
Household food security	Food availability index	0.4079	0.8113	0.6582
	Food accessibility index	0.3061	0.8185	0.6699
	Food utilisation index	0.6190	0.8761	0.7676
	Food stability index	0.5441	0.8421	0.7091

Discriminant validity—Cross loadings

Indicator variables	Extension service quality	Climate smart adaptation	Efficiency of production	Household food security
Tangibility	**0.8321**	0.5019	0.1494	0.4631
Reliability	**0.8304**	0.2120	0.0785	0.1925
Responsiveness	**0.8258**	0.1929	0.0590	0.2408
Assurance	**0.8685**	0.2789	0.0966	0.3522
Empathy	**0.8520**	0.3144	0.2629	0.2468
Improved crop variety	0.2238	**0.8686**	0.0918	0.3395
Optimal fertilise use	0.1613	**0.9445**	0.1270	0.1237
Optimal pesticide use	0.3220	**0.8132**	0.0943	0.3025
Changing planting dates	0.2193	**0.8363**	0.1088	0.3413
Shade tree management	0.1937	**0.7261**	0.0099	0.2051
Crop diversification	0.0064	**0.8140**	0.0510	0.0622
Non crop diversification	0.0806	**0.7032**	0.0934	0.1162
Off farm diversification	0.0799	**0.8589**	0.0765	0.0027
Technical efficiency	0.0815	0.3098	**0.8459**	0.1933
Allocative efficiency	0.1730	0.5961	**0.9615**	0.0885
Food availability index	0.0924	0.0029	0.0282	**0.8589**
Food accessibility index	0.0860	0.0408	0.0095	**0.8113**
Food utilisation index	0.3827	0.4057	0.1479	**0.8185**
Food stability index	0.3611	0.3823	0.0796	**0.8761**

Source: Field survey, Inkoom (2019)

C) Assessment of the structural or latent model

Correlations between latent variables

Variables	Extension service quality	Climate smart adaptation	Efficiency of production	Household food security
Extension service quality	1			
Climate smart adaptation	0.852	1		
Efficiency of production	0.791	0.831	1	
Household food security	0.744	0.767	0.716	1

Summary of the structural model indices

Variable	Type	R squared	Block communality	Mean redundancy	AVE
Extension service quality	exogenous	0	0.709	0.0000	NA
Climate smart adaptation	Endogenous	0.714	0.724	0.4077	NA
Economic efficiency	Endogenous	0.702	0.510	0.3018	NA
Household food security	Endogenous	0. 689	0.730	0.1068	NA

Source: Field Survey, Inkoom (2019)