Does Commodity Diversification Influence Technology Adoption? Evidence from producers in South Carolina

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Introduction

Growth within the agricultural industry relies more on technological advancements than the broader United States (US) economy (Fuglie, MacDonald & Ball 2007). The ability of agricultural producers to maintain higher levels of output while minimizing costs have resulted in increases in adoption rates for new technologies (Mundlak 2000; Pardey at el. 2010; Fuglie & Wang 2012; McFadden, Njuki & Griffin 2023). Although the accessibility and application of technology in agriculture has grown, the use of such technologies is not yet widespread (Schimmelpfennig & Ebel 2011). Several studies have sought to estimate adoption rates and effects of adoption on economic (e.g. yield and profit) and environmental outcomes (e.g. emissions reductions and expenses) but have focused on single commodities or farm units (Dinar & Yaron 1992; Llewellyn & Brown 2019; DeLay, Thompson & Mintert 2021; Torres 2022; Boyer et al. 2024), or even on similar topics such as adoption of technologies that combat climate change, which are focused on environmental welfare and/or potential returns and/or risk preferences and often include compensation (Hall and Wreford, 2012; Roesh-McNally et al., 2017; Mase et al., 2017; Adusumilli and Wang, 2018; Plastina et al., 2018, Thompson et al., 2020; Soh, Wade & Grogan 2023).

Previous literature has investigated the barriers of adoption. This literature finds cost and knowledge may be the leading drivers of non-adoption (Gillespie, Kim & Paudel 2007; Groher et al. 2020; Rosa 2021; Makinde 2022) Agricultural producers' willingness to adopt technologies is well defined in the literature and models have been generated with proven variables that explain these adoption rates.

This specific research lacks perspective on the impact of commodity diversification (or multi-enterprise production) on technology adoption. To fill this gap, we estimate the relationship between multi-enterprise production and technology adoption for a diverse group of producers in South Carolina using a dataset generated from survey results from a United States Department of Agriculture (USDA) Natural Resources Conservation Service (NRCS) Climate-Smart commodities program during the summer of 2023. In this study, we are interested in identifying whether diversification of commodity production, or multi-commodity production, influences technology adoption decisions made by South Carolina agriculture producers. We are not aware of any previous study that has explored this factor.

We model South Carolina producer technology adoption based on responses to a survey of enrolled producers in an USDA-NRCS Climate Smart commodities program. The Climate-Smart commodities program is an incentive-based program that aims to expand the markets for America's climate-smart commodities, leverage the greenhouse gas benefits of climate-smart commodity production, and provide direct and meaningful benefits to production agriculture (USDA 2023). Survey responses were gathered in Fall 2023 by Clemson University who sent the survey to all producers participating the South Carolina Climate-Smart commodities program.

All producers in the sample are guaranteed to produce at least one commodity and could also produce livestock, row crops, fruits, vegetables, and forest separately. We test whether multi-commodity production for South Carolina producers increases technology adoption using an ordered logit regression model to determine increases and decreases in the probability of adoption as producers diversify production. The producers represented in the sample are representative of the South Carolina population and show variance in production decisions based on enterprises ranging from forestry production to fruit, vegetable, livestock, and row crop production. The incorporation of multiple enterprises on the farm will be captured by the model.

This analysis will add to the current literature by examining producers and how the diversification of enterprises invested in affects adoption decisions. Specifically, we analyze how diversification of commodities affects technology adoption among producers with results that indicate that diversification of commodities produced on the farm does influence technology adoption rates for producers. The overall objective of this paper is to evaluate commodity diversification and its influence on technology adoption for farmers in South Carolina with the use of survey data from the Climate-Smart enrolled producer survey. Estimate the effect that commodity diversification has on the probability of technology adoption block rates for farmers in South Carolina. Higher rates of commodity diversification increase the probability of technology adoption block rates for South Carolina farmers.

Methodology and Data

Survey

This study was conducted in South Carolina where we explore producers' willingness to adopt agricultural technologies. Producers were selected for the Climate-Smart commodities program based on application timeline and must have applied before the late spring 2023 deadline to be enrolled in the program. For the livestock program, three production practices were offered (incorporation of legumes, nutrient management, and prescribed grazing). The enrolled peanut producer's production practices included cover cropping and residue and tillage management while the leafy greens section included cover cropping, reduced tillage, and mulching. Producers participating could choose to participate in any or all production practices within their section listed above but could not be enrolled in more than one program. As an example, producers registered for the beef cattle program program were not permitted to join the peanut or leafy green programs with the intent of collecting two payments. Enrolled producers were required to complete this enrolled producer survey to continue their enrollment in the program.

In fall 2023, producers enrolled in the program were given a survey to be completed by all participants in the program. The survey collected information on socio-demographics, farmer characteristics, farm characteristics, production goals and methods, financial information, and risk preferences. Socio-demographic questions included in the survey were questions regarding marital status, level of education, ethnicity, age, and gender. Farmer characteristic questions were asked to gain information on occupation and interactions and attitudes with extension. Questions asked with the purpose of identifying farm characteristics were location, total area of the farm and area in production, organic vs nonorganic, acres owned vs leased, lease payment and lease length and land rented to others.

Production goals and method questions included questions that asked for the approximate annual acreage for each commodity produced on the farm. The question structure used to get this information was broken into pieces for ease of the participant. First, the participant was asked "Which of the following do you produce?" and could select from row crop, vegetables, fruit or orchard, livestock, and forestry. Each commodity group had a second question that listed various types of commodities within the commodity group and asked for approximate annual acreage for each commodity. Another box was included where producers could also fill in commodities and acreages for were not included in the list. The same design for livestock was used but asked about head counts rather than acreage. A separate question asked for total acres used for livestock. All participants also saw a question with the 14 technologies listed in table 1 below and asked whether they have implemented or adopted the said practice. The participant could choose yes, no, or interested.

Econometric framework

We used the Ordered Logistic Regression model to test whether diversification of commodities increases technology adoption on the farm among producers in the state of South Carolina. The dependent variable is an ordinal variable and is dependent on how many technologies each producer adopted while the independent variables are a combination of both continuous and binary variables. The ordered logistic model that we use (Habib, Alauddin, Muriithi, Cramb, Rankin 2022) is specified below.

$$\Pr(Yi > j) = \frac{\exp\,(aj + Xi\beta j)}{1 + [\exp(aj + Xi\beta j)]}\; j = 0 - 7$$

Where Yi = the dependent variable reflecting the 7 levels of technology adoption (adoption of: 0, 1, 2, 3, 4, 5, 6 blocks) by producers in the sample.

Yi=0 Producers who have not adopted any technology block

Yi=1 Producers who have adopted 1 technology block

aj = the intercept term, βj vector of parameter to be estimated and X denotes independent variables.

Data

There was a total of 14 technologies that producers were asked if they had adopted. Once the survey was conducted, the 14 technologies were aggregated into six different technology adoption blocks shown in table 1 below.

Table 1: Technologies and Block generation

Blocks	Technologies within the block
Data Collection	• Soil or plant moisture sensors • Weather monitoring with weather stations • GIS technology
Input Management	• (Plastic) mulching • Alternative freeze protection (wind machines, tunnels, row covers)
Irrigation	• Variable rate irrigation • Automatic irrigation system with timer or controller
Guidance	• Auto steer • GPS technology
Automation	• Auto feeding • Automated environmental controls for animal housing
Farm Management	• Computers to track data or manage finances • Smartphones/tablets for farm management • Blockchain technology

To generate the dependent variable used in this analysis which reflects South Carolina producers' technology adoption, producers were separated and ordered into groups based on how many of the above blocks that they have adopted on their farm. These groups are (0) - Adopted 0 technology blocks; (1) - adopted 1 technology block; (2) - Adopted 2 technology blocks; (3) - Adopted 3 technology blocks; (4) - Adopted 4 technology blocks; (5) - Adopted 5 technology blocks; (6) - Adopted 6 technology blocks. Table 2 below shows the adoption rate for each technology individually and as a block. The table shows that many of the producers in the survey are adopting technologies within the farm management block more compared to the other technologies available. We found that 24.76% of the survey respondents have not adopted any of the technologies available while 26.67% of respondents have adopted at least one technology.

Table 2: Means of dependent variable classifications

BLOCKS AND TECHNOLOGIES WITHIN EACH BLOCK	OVERALL MEANS
DATA COLLECTION BLOCK	**32.86%**
SOIL AND PLANT MOISTURE SENSORS	14.76%
WEATHER STATIONS	17.14%
GIS	17.62%
INPUT MANAGEMENT BLOCK	**19.52%**
(PLASTIC) MULCHING	15.24%
ALTERNATIVE FREEZE PROTECTION	11.43%
IRRIGATION BLOCK	**22.38%**
VARIABLE RATE IRRIGATION	9.05%
AUTOMATIC IRRIGATION SYSTEM	17.14
GUIDANCE BLOCK	**37.62%**
AUTO-STEER	22.38%
GPS	37.14%
AUTOMATION BLOCK	**7.14%**
AUTO FEEDING	5.71%
AUTOMATED ENVIRONMENTAL CONTROLS	4.29%
FARM MANAGEMENT BLOCK	**51.90%**
PHONE/TABLET	45.24%
COMPUTER	37.62%

BLOCKCHAIN	1.43%
ORDERED LOGIT CATEGORIES	
ADOPT 0 BLOCKS	**24.76%**
ADOPT 1 BLOCK	**26.67%**
ADOPT 2 BLOCKS	**21.90%**
ADOPT 3 BLOCKS	**12.38%**
ADOPT 4 BLOCKS	**8.10%**
ADOPT 5 BLOCKS	**5.78%**
ADOPT 6 BLOCKS	**0.48%**

Results and Discussion

Table 3 below shows the independent variables that we have included in our model and their proportions based on the enrolled program of the producer.

Four of our independent variables are included to explain farmer characteristics. *Upstate* is a binary variable equal to 1 if the majority of the producer's farm is in the Upstate region of South Carolina, 0 if the majority of farm is in the lower state. This variable was included in the model to consider regional differences within the state. *Education* is a binary variable equal to 1 if the producer who enrolled in the program has obtained a bachelor's degree or higher. This variable is a measure for education. *Fulltime* is a binary variable equal to 1 if the producer reported having no employment off the farm. *Age* is a continuous variable added to the model to control for differences in adoption rates based on age.

OwnProperty, and size of farm based on sales are variables included in the model to explain farm characteristics. *OwnProperty* is a binary variable equal to 1 if the producer owns the land that they farm, 0 otherwise. *SalesExSmall* is a binary variable equal to 1 if the average yearly gross value of sales for the operation is less than $25,000, zero otherwise. *SalesSmall* is a binary variable equal to 1 if the average yearly gross value of sales for the operation is between $25,000 – $349,999, zero otherwise. *SalesMedium* is a binary variable equal to 1 if the average yearly gross value of sales for the operation is between $350,000 - $999,999, zero otherwise. *SalesLarge* is a binary variable equal to 1 if the average yearly gross value of sales for the operation exceeds $1,000,000, zero otherwise. The sales variables outlined above are included in the model as a variable that explains the operations size.

The five production independent variables below aim to capture diversification of commodities of producers. *Fruit, Forest, Vegetable and Rowcrop* are all binary variables equal to 1 if the farmer produces each respective commodity, 0 otherwise. These variables capture producer production decisions and explain each farm's multi-commodity structure, or lack of. The variable *Livestock* is omitted from the model given that all producers in the survey produce livestock. We do have producers within this sample that exclusively produce livestock. The variable *TotCount* is included in the model and is a count variable that is equal to the total number of different commodities that the producer produces.

Table 3: Summary statistics for independent variables by enrolled program

ENROLLED PROGRAM:	**BEEF CATTLE**	**LEAFY GREENS**	**PEANUTS**	**OVERALL MEANS**
VARIABLES:				
Upstate	0.24	0.10	0	0.15
Midlands	0.25	0.10	0	0.16
PeeDee	0.27	0.37	0.42	0.32

LowCountry	0.24	0.43	0.58	0.37
Age	55.64	56.71	46.42	54.42
Education	0.57	0.37	0.58	0.50
Fulltime	0.47	0.55	0.53	0.50
OwnProperty	0.88	0.77	0.72	0.82
Livestock	1	0.27	0.36	0.64
Fruit	0.05	0.25	0.06	0.12
Forest	0.53	0.32	0.56	0.47
Vegetable	0.07	0.89	0.06	0.34
Rowcrop	0.19	0.49	1	0.43

Full econometric results will be presented and discussed at the in-person presentation.

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