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THREE ESSAYS ON HEALTH, FOOD, AND AGRICULTURAL ECONOMICS

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THREE ESSAYS ON HEALTH, FOOD AND AGRICULTURAL ECONOMICS

DISSERTATION

A dissertation submitted in partial fulfillment of the
requirements for the degree of Doctor of Philosophy in the
College of Agriculture, Food and Environment
at the University of Kentucky

By

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Lexington, Kentucky

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Lexington, Kentucky

2023

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ABSTRACT OF DISSERTATION

THREE ESSAYS ON HEALTH, FOOD, AND AGRICULTURAL ECONOMICS

This dissertation comprises three distinct but interrelated projects that explore the intersection of agriculture, nutrition, and economics. The first project investigates the impact of Community Supported Agriculture (CSA) food programs on the health outcomes of its participants. Using fixed effects models and a matching algorithm, the study finds that while conventional fixed effects models indicate a significant effect of CSA participation on diet-related medical expenditures, our modified time-heterogenous fixed effects model did not find a meaningful effect. The results of the matching method are consistent with those of our modified model.

The second project examines racial disparities in the prevalence and management of diabetes among Supplemental Nutrition Assistance Program (SNAP) participants. The study shows that minority groups, including American Indian or Alaska Native adults, Hispanics, and non-Hispanic Blacks, have higher rates of diabetes than non-Hispanic whites in the US. Additionally, the study reveals that SNAP participants follow a cyclical pattern in food consumption and dietary habits, which may complicate diabetes control. The findings underscore the need to address the ethnic-specific behavior of SNAP participants in diabetes management to address the racial disparity in diabetes prevalence and management.

The third project explores the differences between auction venue channels on sale prices. Using a Two-Stages Least Squares method and a switching regression model, the study finds that different auction venues directly cause selling price differentiation. Equipment-specific attributes significantly influenced planters' sale prices within sale venues, and equipment-specific characteristics, financial attributes of state farming, and geographical features affect planters' auction selection. The study's findings are useful for sellers and buyers seeking the most profitable sales venues for their planter sales.

Understanding the dispersion of prices specific to each auction venue can lead to better venue decision-making, especially with the growing trend of web-based auctions.

Overall, this dissertation highlights the importance of examining the intersection of agriculture, nutrition, and economics to better understand the impact of various policies and programs on public health and economic outcomes.

KEYWORDS: food policy, CSA, SNAP, auction, diabetes, health.

Saber Feizy

04/17/2023

Date

THREE ESSAYS ON HEALTH, FOOD, AND AGRICULTURAL ECONOMICS

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Date

This humble work is dedicated to:
The ancestors who paved the path before me upon whose shoulders I stand.
Atiyeh and Fatemah, my little heartfelt family, my life, my home.
My Parents, brothers, and the many Friends who supported me on this journey.

And above all,
To the Almighty God, his Messenger Muhammad and his Family (PBUT), and all the Shohada.

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I am grateful to Allah the most Merciful the most Compassionate, for all the countless blessings He has bestowed upon me. The One who created the data of my life, artfully crafted the environment in which I live, directed me toward the right model, and blessed me with a heartfelt outcome, my little beloved family, Atiyeh and Fatemah.

I would like to express my sincere gratitude to all those who have contributed to the completion of this work. I would specially thank to Dr. Mark and Dr. Zhao, my dissertation co-advisors, for their unwavering support, invaluable guidance, patience, encouragement, and efforts that have been instrumental in making this work possible. I am deeply grateful for their constant and unconditional support in my personal and academic life, especially during the ups and downs throughout the years of completing my PhD.

I am also grateful to the members of my dissertation committee, Dr. Woods, Dr. Pates, Dr. Zheng, and Dr. Bastin, for their worthful feedback and suggestions. I would also like to extend my gratitude to the many people who contributed to this dissertation, directly or indirectly, i.e., my classmates, collaborators, and all AEC members for their support and encouragement.

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CHAPTER 1. INTRODUCTION

Health has always been a significant concern for humans. A tremendous number of research studies have explored different facets of public and individual health, including its issues that overlap with food, and consequently, the agricultural sector. Consuming healthy food products, enrolling in food-health-based programs, and receiving food-health-related payments, are common issues between health and food. This dissertation studies two interconnected issues between agriculture and health sectors, looking specifically at the econometrics methodologies.

Chapter 2 introduces a new empirical model to address the heterogenous-time fixed effects bias in panel data settings resulting from the mean reversion and provides new insights into the heterogeneous effect of participating in a Community Supported Agriculture (CSA) on health outcomes. CSA is a program that is generally considered a transformative market for small-scale farmers to get directly in touch with consumers. In our application, CSA, program participants with high baseline medical expenditures appear to benefit significantly from participating in the CSA, while the effects are less pronounced for individuals with lower baseline expenditures. In the high baseline expenditure group, participants may have had a positive shock to their expenditures in the periods immediately preceding their CSA participation; thus, such participants will tend to revert to their mean historical expenditure levels naturally. This phenomenon is known as mean reversion.

Mean reversion appears when subsamples experience a time-specific shock and return to their mean values over time. This can result in misleading estimates of causal effects in the standard form of panel data analysis and cause biased effect estimates. I contrast the performance of the conventional fixed effects model with our modified heterogenous-time fixed effects model to see which model can mitigate the heterogeneity bias arising from mean reversion. I consider the robustness of our results via a placebo test and a genetic matching algorithm.

Chapter 3 exhibits an analysis of racial disparities in health outcomes resulting from participating in the Supplemental Nutrition Assistance Program (SNAP) among the lower income population in the US. In particular, getting involved in the SNAP program and the time schedule of receiving the SNAP benefits would be expected to impact how the participants with diagnosed diabetes would manage their diabetes levels. To capture such impacts, I utilize the National Health and Nutrition Examination Survey (NHANES) dataset over 2007 to 2018. The findings of this study may inform policy decisions related to health with respect to low-income minorities.

Chapter 4 brings attention to market selection problem and how it can affect the sale prices. This study has two main goals. Firstly, it seeks to determine whether price differentiation occurs based on the different selling markets. Secondly, it aims to quantify the extent to which each available selling market affects the final selling price. To achieve these goals, the study utilizes data from various types of auctions and their corresponding daily transactions on used planters. The analysis employs two methods: a two-stage least squares model and a switching regression with endogenous switching model. The results from this analysis provide a clearer picture of the factors that influence the seller's optimal marketing platform, and can inform the agriculture sector's regulators. Finally, I provide concluding remarks from these analyses in Chapter 5 and provide policy implications.

CHAPTER 2. MEAN REVERSION IS MISLEADING: THE TRUE EFFECT OF A COMMUNITY SUPPORTED AGRICULTURE FOOD PROGRAM ON HEALTH

2.1 INTRODUCTION

Increased attention has been paid in recent years to address mean reversion in the econometric settings. A segment of this work focuses on implementing fixed effect models to neutralize mean reversion in panel data sets. An often-overlooked aspect in this space is the time-heterogenous component of mean reversion in panel datasets. In this study, I develop an empirical model to address the heterogeneous-time bias that emerges from mean reversion in panel data settings. I apply this model to data on the weekly consumption of Community Supported Agriculture (CSA) food program over 2015 and 2016 and account for the underlying baseline health conditions by separately considering subsamples with high and low-health conditions.

2.1.1 CSA

The United States experienced a significant rise in healthcare expenses (PGPF, 2020; Tohid & Maibach, 2021). The growing cost of healthcare is largely driven by diet-related medical expenses. These can be attributed to factors such as physical inactivity, obesity, smoking, and alcohol (Lloyd, 2018). In response, many employers implement wellness programs to reduce healthcare spending, including CSA food programs (Berry et al., 2010; Parks & Steelman, 2008). As evidenced in numerous studies (e.g., Berkowitz et al., 2019; Perez et al., 2003; Sarwar et al., 2015), healthy dietary habits are linked to a lower risk of diet-related health problems, including hypertension, diabetes, and obesity. Despite this, no research has examined the direct impact of participating in a

CSA food program on health outcomes. Notably, incorporating fresh, healthy produce through a CSA food program could potentially lower hospital and clinical visits, which in turn can lead to decreased medical expenses.

To achieve this goal, the University of Kentucky's Health and Wellness Program recently implemented a produce-based Community Supported Agriculture food program to promote healthier eating habits among its employees. CSA programs have become increasingly popular in the US over the past few decades, with the total number of CSA farms growing from around 1,900 in 2008 to over 7,300 in 2017 (DeMuth, 1993; Hammonds, 2017). While there is growing interest in CSA programs, much of the research on their impacts has been descriptive or based on case studies of a small number of farms.

To fill this gap, this study seeks to analyze data from employees who participated in the CSA food program through the University of Kentucky's H&W Program in 2015 and 2016 in order to evaluate the potential of CSA food programs as a wellness intervention. In this study, I will answer three questions: (1) Does participating in the CSA food program lead to improved health outcomes? (2) Is the impact of CSA uniform across all participants, or does it vary among subgroups? (3) Is there any evidence of mean reversion, and if so, can it be mitigated in the analysis? Due to data constraints, this research will focus on the short-term effects of the CSA intervention. This study's findings offer important insights into the feasibility of CSA food programs as a viable wellness intervention.

2.1.2 Mean Reversion

Mean reversion, the tendency of a variable to return to its average value over time, has been empirically studied in various areas (Balvers et al., 2000; Fama & French, 1988; Poterba & Summers, 1987). However, mean reversion is often overlooked in panel models, particularly in models with heterogeneous treatment effects. Failing to account for mean reversion can bias heterogeneous treatment effect estimates. The impact of mean reversion is of particular importance in our study given we are focusing on the effect of participating in a CSA program on dietary changes that could potentially result in reduced medical expenses. Understanding and accounting for mean reversion is critical as it could influence the observed changes in dietary behavior and health outcomes over time. Failure to consider mean reversion could lead to inaccurate conclusions about the effectiveness of CSA programs in promoting healthier diets and reducing medical expenses.

This analysis suggests that the effects of the CSA program on health vary depending on the baseline health condition. In particular, participants who have high baseline medical expenses, i.e., those with poorer health conditions, benefit more from the program than those with lower baseline expenses, i.e., those with better health conditions. I find that this differential impact is driven, at least in part, by mean reversion. On an individual basis, medical expenses are often lumpy over time. Individuals with lower expenses before participation may have pent up medical expenses to make after participation. Conversely participants with high medical expenses before participation may not need the same medical or expenses after participation. A failure to account for mean reversion can lead to a spurious conclusion that the CSA program significantly lowers medical expenses for all participants.

2.2 DATA

I utilized a panel dataset of medical claims from University of Kentucky (UK) employees who participated in the CSA food program conducted by UK Health and Wellness (H&W) from 2015 to 2016. I identified all possible participants from individuals who provided the H&W permission to utilize their claims records in research studies. The study included a random group of participants who received a $200 CSA voucher through the H&W's wellness check-in program.

I obtained anonymized claims of CSA participants who permitted H&W to use this information in research projects. I collected claims on two groups of employees: a treated group of CSA voucher participants and a control group of non-participants. I acquired claims from all employees registered with H&W program but not receiving the CSA voucher to serve as our controlled group over the same period.

To isolate the impact of the CSA program on diet-related medical expenditures, I consulted with public H&W professionals to determine which medical claims were explicitly related to diet. This allowed me to remove claims related to high-cost conditions with no direct link to acute dietary changes such as orthopedic surgery, chemotherapy, physical therapy, etc. I only included billed amounts from services, diagnoses, and diet-related drugs from medical claims where any clinic and hospital visits and claims related to hypertension, obesity, and/or diabetes were considered diet-related medical expenditures. A summary of descriptive statistics is reported in Table 2-1.

I then divided the dataset into two subgroups: high and low risk based on a threshold of the average value of the baseline diet-related medical expenditures for all participants. Table 2-2 summarizes participants with high and low baseline diet-related medical expenditure ($/six-month). The billing periods were divided into three baseline (pre-intervention) periods and three intervention periods, with all time slots being six-month blocks. I removed all outliers whose diet-related medical expenditures were above the 99th percentile from the analysis.

2.3 METHODOLOGY

I estimate the impact of participating in a Community Supported Agriculture (CSA) program on dietary changes and medical expense outcomes using a fixed effects model with panel data.

2.3.1 Fixed effects (FE)

In the fixed effect model, the common approach to estimate the treatment effect on the outcome variable is to regress the outcome variable on the treatment indicator, time variant fixed-effects, and individual-specific time-invariant fixed-effects as in $y_{it} = \hat{\beta}_0 + \hat{\beta}_1 Tr_{it} + \hat{\gamma} X_i + \hat{\mu}_i + \hat{\tau}_t + \varepsilon_{it}$ where i and t represent individuals and time, respectively, y_{it} is the outcome variable, Tr_{it} is the treatment indicator, X_i is a vector of covariates that influence the outcome variables, μ_i are individual fixed effects, τ_t are time fixed effects, and ε_{it} are all unobservable characteristics (Angrist & Pischke, 2008). However, this approach can be naïve if the treated units heterogeneously impact the outcome variable. Since treatment effects can vary by baseline health conditions in CSA context, I separately estimate the impact of the CSA program based on diet-related medical expenditures for individuals with high and low baseline health condition. I expect individuals with higher baseline expenditures to benefit more from the program than those with lower baseline expenditures. To estimate these effects, I follow a common approach and interact the treatment indicator with categorical variables corresponding to baseline levels of diet-related medical expenditures via equation (1) as follow:

$$y_{it} = \hat{\beta}_0 + \hat{\beta}_1 Tr_{it} L_i + \hat{\beta}_2 Tr_{it} H_i + \hat{\gamma} X_i + \hat{\mu}_i + \hat{\tau}_t + \varepsilon_{it} \tag{1}$$

Where i and t represent individuals and time, respectively, y_{it} is the outcome variable, Tr_{it} is the treatment indicator, L_i and H_i indicate that individual i is in the low or high pre-intervention period expenditure category, respectively, X_i is a vector of covariates that influence the outcome variables, μ_i are individual fixed effects, τ_t are time fixed effects, and ε_{it} are random errors.

2.3.2 Heterogenous-Time Fixed effects (HTFE)

Estimating heterogeneous treatment effects via equation (1) is vulnerable to heterogeneous time fixed effect bias. The issue can be seen more clearly by considering the types of unobservable variables controlled with fixed effects. The time fixed effects control for time-specific shocks common to all observations in a given period.

This means that the same time-specific shock affects all individuals/units within a given period, regardless of their characteristics or treatment status. As a result, if the treatment effect varies across groups or individuals, the fixed effects may not fully capture these differences, leading to biased estimates. For example, if an intervention has a different effect on individuals with high versus low baseline levels of the outcome variable, and the fixed effects cannot capture these differences, the estimated treatment effect will be biased. Therefore, it is important to develop a method that accounts for the heterogeneity of the treatment effect over time and across different groups or individuals.

To address this issue, I propose a modified estimator that interacts the baseline high and low expenditure groups with the time fixed effects. This allows for separate time-specific shocks for each group, which helps to disentangle the program effect from the mean reversion effect. Generally, the time fixed effect shows a common time shock to all individuals/units. By interacting the time fixed effect estimator with the pre-intervention expenditure category, I can delineate that everyone in the high baseline expenditure group generally experiences a similar reversion to their mean expenditure in the post-intervention period, and likewise for the low expenditure group. Our approach, the Heterogeneous-Time Fixed Effects (HTFE) estimator, is based on a fixed effects model that includes pre-intervention expenditure quintiles interacted with time fixed effects. Specifically, I estimate the HETFE model via equation (2) as follow:

$$y_{it} = \hat{\beta}_0 + \hat{\beta}_1 Tr_{it} L_i + \hat{\beta}_2 Tr_{it} H_i + \hat{\tau}_{1t} L_i + \hat{\tau}_{2t} H_i + \hat{\gamma} X_i + \hat{\mu}_i + \varepsilon_{it} \qquad (2)$$

where y_{it} is diet-related medical expenditures for individual i in the 6-month billing period t, L_i and H_i are indicator variables showing whether individual i is in the low or high pre-intervention period expenditure category, respectively, Tr_{it} is an indicator variable representing whether the individual i has participated in the CSA program in year cohorts 2015 or 2016, τ's are the time fixed effects, and the interaction between τ's (τ_1 and τ_2) and high-low baseline expenditure categories (H_i and L_i) are the time fixed effects corresponding to the high and low pre-intervention period expenditure category.

To visually demonstrate the issue of mean reversion, how it can affect the estimation of average treatment effects, and how our modified estimator can address it, I present Figure 2-1 through Figure 2-5 which uses a synthetic dataset for illustration purposes. Figure 2-1graphically illustrate a mild downward trend in the outcome variable estimated by the ordinary least square method (OLS) for all observations. Later, I split the observations into high- and low-expenditure categories based on the participants' diet-related medical expenditure before the intervention and plotted them in Figure 2-2 and Figure 2-3, respectively. The double-difference method via the conventional model, shown in Figure 2-2 and Figure 2-3, fails to identify any significant impact of program participation on the outcome variable.

However, the modified fixed effects model, which accounts for time fixed effect heterogeneity bias among those in the high- and low-expenditure categories, can significantly impact the outcome, as shown in Figure 2-4 and Figure 2-5. I developed this model to address the mean reversion issue, which is caused by the opposing effects of mean reversion on the outcome variable for those with high and low baseline expenditures. I can distinguish between these two effects using the model developed in equation (2).

2.3.3 Robustness Checks

2.3.3.1 Placebo Test

To verify the robustness of our modified fixed effects model, I conducted a placebo test. Our approach was to remove all CSA members who received the treatment from the dataset and artificially assign treatment to the controlled individuals randomly. I then estimate the FE and HTFE models on the synthetic dataset. If the FE model captures a significant effect and the HTFE model does not, it supports the presence of mean reversion in the dataset.

2.3.3.2 Genetic Matching Algorithm

Observational studies are vulnerable to self-selection bias due to the non-random assignment of entities into treatment and control groups. To mitigate this issue, I use a fixed effects model that adds individual-specific dummies to control for all time-invariant individual-specific features. However, to further support the validity of our findings, I also used a genetic matching algorithm to compare the health status of participants in the CSA food program (treated units) to similar individuals who did not participate in the program (control units). This algorithm involves matching treated individuals with similar untreated individuals, based on their observable characteristics, to create a balanced comparison group.

Matching on correctly specified propensity scores balances the observed covariates by making the treatment and control units to have the same joint distribution of the observed covariates, asymptotically. The true propensity score is generally unknown, and one would have to estimate it. Genetic matching method is a process of iteratively modifying the estimated propensity scores to maximize the covariate balance. Genetic matching method is a generalization of propensity score and Mahalanobis Distance matching and uses an evolutionary genetic search algorithm developed by Sekhon and Mebane (1998) to maximize the balance of observed covariates across the matched treatment and control units.

The propensity score is the conditional probability of treatment assignment given the covariates. The propensity score is a balancing score where it asymptotically balances the observed covariates conditioning on the true propensity score. Therefore, if matching on propensity score does not asymptotically balance the observed covariates, the estimates of the propensity score is inconsistent. Therefore, assessing covariate balance in the matched sample (via F-ratios, likelihood ratios, etc.) and using proper approaches to achieve acceptable balance is essential in getting consistent estimates (Diamond & Sekhon, 2013). One way to obtain balance of the covariates is to use a combination of propensity score and a Mahalanobis Distance matching by including the estimated propensity scores among the covariates to obtain balance on the covariates (Rosenbaum & Rubin, 1983).

The genetic matching method developed by Diamond & Sekhon (2013) uses a genetic algorithm to search a range of distance metrics to find the specific measure that optimizes post-matching covariate balance, then, assigns a weight to all matching variables according to their relative importance for achieving the best overall balance (Diamond & Sekhon, 2013).

2.3.4 Estimation Strategy

A propensity score matching reflect the probability of each individual being treated. To estimate the propensity scores, I used a logistic regression model and match each treated unit with one or more control units with similar propensity scores, taking care to ensure that the matching process balanced the observable characteristics of the treated and control units. Specifically, I checked the balance of key covariates such as pre-intervention diet-related medical expenditures for each 6-month billing period, the number of doctor visits, year of birth, and gender, to ensure that there were no remaining confounding variables.

To estimate the propensity score, I first estimate the logistic regression, $\Pr(Tr_i = 1|Z_i) = \Phi\{h(Z_i)\}$, where Tr_i is the treatment status of individual i which takes 1 if the participant received treatment and 0 otherwise, Φ denotes the logistic CDF, and $h(Z_i) = \hat{\alpha}_0 + \sum_{k=1}^{3} \hat{\alpha}_k exp\_pre_{ik} + \sum_j \hat{\alpha}_j X_j$ is a specification that includes all the covariates (Z_i) in which exp_pre_{ik} is the baseline diet-related medical expenditure in period k for individual i, X_j is a vector of other covariates including age, gender, and the number of visits to the doctor during pre-intervention periods, $\hat{\alpha}$'s are the corresponding coefficients.

I then use the estimated propensity score and include them in the Mahalanobis Distance method as another covariate. Formally,

$$GMD(V_i, V_j, W) = \sqrt{\left(V_i - V_j\right)^T (S^{-1/2})^T W S^{-1/2} \left(V_i - V_j\right)}$$

Where GMD stands for the Generalized Mahalanobis Distance, W is a $k \times k$ positive definite weight matrix, S is the sample covariance matrix of Z, $S^{-1/2}$ is the Cholesky decomposition of S, that is, $S = S^{-1/2}\left(S^{-1/2}\right)^{T}$, and V is a matrix consisting of both the estimated propensity score and the underlying covariates (Z).

It is worth noting that the genetic matching algorithm is equivalent to propensity score matching if the optimal balance is obtained by only matching on the propensity score matching. In this case the other variables will be given a zero weight. Alternatively, the genetic matching method would be equivalent to minimizing the Mahalanobis Distance and may converge to assigning zero weight to the propensity score and one to every other variable in Z.

2.4 RESULTS AND DISCUSSIONS

This research paper aims to investigate the impact of participation in a CSA food program on diet-related medical expenditures. To this end, I utilized a fixed effect model and modified it to detect any heterogeneous effects that may result from mean reversion. I also employed a placebo test and a nonparametric approach to confirm the consistency of our findings. The goal of this study was to determine not only if CSA participation leads to a significant reduction in medical expenses, but also to identify any potential subgroups that may exhibit different responses to the program.

2.4.1 FE and HTFE Results: Evidence of Mean Reversion

The findings of estimating models (1) and (2) are presented in Table 2-3 and Figure 2-6. The results of the FE model, which includes control variables, individual fixed effects, and time fixed effects, show that most estimated coefficients of the variables of interest are negative. Interestingly, the estimated coefficients of high-baseline diet-related medical expenditures in both 2015 and 2016 and in the aggregate data are statistically significant, suggesting a significant effect of participating in a CSA food program on diet-related medical expenditures.

Our analysis indicates a significant effect of CSA participation on diet-related medical expenditures for high baseline participants. The fixed effects model shows that medical expenses drop dramatically after CSA participation for both 2015 and 2016 high baseline participants. However, CSA participation is not statistically beneficial for low baseline participants in terms of decreasing their diet-related health expenses. This heterogeneous effect may be due to the targeted CSA providers population being those participants with higher baseline expenditures, who experience the most benefit from the program.

The HTFE model does not find any evidence that CSA participation influences short-run diet-related medical expenditures for either high or low-baseline medical expenditure subgroups in either 2015 or 2016 or the aggregate data. These results indicate heterogeneous time fixed effects in participants with high versus low-baseline medical expenditure and are reflected by the inclusion of time fixed effects interacted with baseline expenditure status in the model. The modified fixed effects analysis highlights the mean reversion issue and its potential to mislead model estimations if not properly addressed. By adding time interval expenditure interactions to the model, I were able to reduce bias and support our primary claim that addressing mean reversion may change the estimation of effects obtained using naive models toward the true effects.

One possible reason for the lack of a significant short-term impact of CSA participation on diet-related medical expenses is the concept of time inconsistency. Previous research has shown that time inconsistency, or the tendency for present and future biases to influence consumer behavior, may cause people to not consume healthy food (Madrian & Shea, 2001; Shui & Ausubel, 2004; Khwaja, Silverman, & Sloan, 2007). In the context of this study, it was expected that participating in a CSA program and regularly receiving a healthy vegetable box would lead to a reduction in diet-related medical expenditures. However, it is possible that other factors such as busy schedules prevented participants from consuming the healthy produce when it was fresh. This may have contributed to the lack of a significant impact on medical expenses in the short term.

2.4.2 Placebo Test Results

The results of the placebo test, shown in Table 2-4, provide evidence of the existence of mean reversion and the ability of the modified HTFE model to capture this issue and give an unbiased estimator. Our findings from the placebo test show that the conventional fixed effect model in column (1) estimates a significant negative effect of high baseline expenditure on diet-related medical expenditures. However, the modified HTFE model in column (2) does not find a significant effect on diet-related medical expenditure for either low or high baseline expenditure subgroups. This is because the modified model includes time interval by baseline expenditure fixed effects, which controls for mean reversion behavior in the dataset. The findings of the modified HTFE model are consistent with the results of the placebo test.

2.4.3 Robustness Check with Genetic Matching Algorithm

The results of the matching process are reported in Table 2-5. Panel A shows that the mean differences between control and treatment units decreased after matching the treated participants who actively received CSA deliveries and control individual who were CSA non-participants. The results from the balance table reports the differences between the control and treated participants in the match variables for both before and after match. The results indicate that the genetic matching algorithm found acceptable matches to the treated participants. Panel B reports the estimated average treatment effects on treated participants (ATT). All estimated ATTs were statistically non-significant, which further support our argument on the modified HTFE model that there is no identifiable evidence that CSA participation results in a significant decrease in short-term diet-related medical expenditures.

2.5 CONCLUDING REMARKS

Overall, our study has contributed to a clearer understanding of the mean reversion phenomenon and developed a new empirical model to neutralize mean reversion in panel data settings in order to obtain unbiased estimates. Additionally, this study has provided new insights into the heterogeneous effect of participating in a CSA food program on health outcomes, i.e., diet-related medical expenditures.

Our analysis showed that mean reversion was present in the data, and as a result, a modified fixed effects model was necessary to accurately estimate the true treatment effect. Our results showed that participating in CSA may not result in a significant reduction in diet-related medical expenses in the short term, a finding that was supported by placebo tests and a robustness check with a nonparametric approach, i.e., matching method. While our findings show that CSA participation did not have a significant impact on diet-related medical expenses in the short run, it's important to note that there may be other benefits to participating in CSA programs for both consumers and producers. A CSA food program is still a valuable way to support local agriculture and access fresh produce. Additionally, the long-term effects of participating in a CSA program has to be further studied.

The lack of available data prevented us from examining the long-term effects of CSA participation on health outcomes and limited the generalizability of our homogeneity findings. Despite the limitations, our findings have important implications for CSA incentive program developers, as they suggest that the short-term impacts of such programs on health outcomes may be more modest than previously thought. Further research is needed to fully understand the relationship between CSA participation and health expenses. Future studies could explore the long-term effects of CSA participation on health outcomes to overcome data limitations.

2.6 Figures

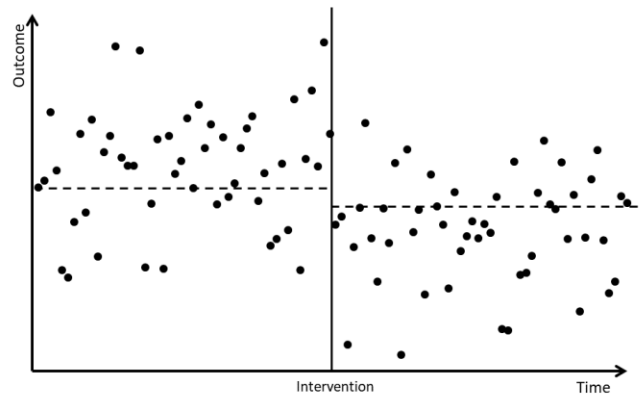

Figure 2-1. Synthetic dataset that suffers from mean reversion issue

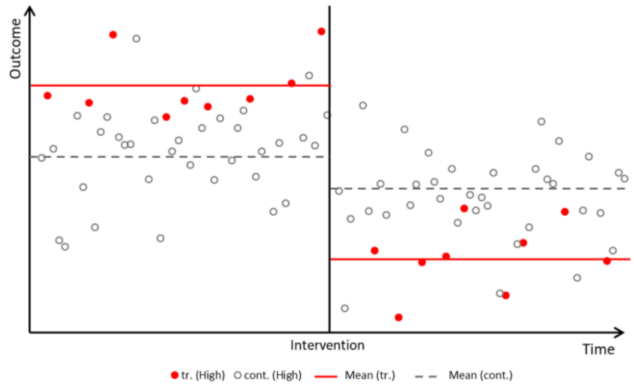

Figure 2-2. Naïve FE Estimation of High Baseline Group

Note: Treated and controlled observations and corresponding means in pre- and post-intervention periods in High expenditure category of the naïve model

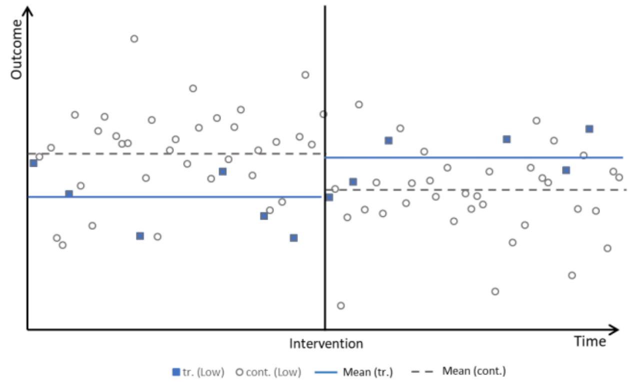

Figure 2-3. Naïve FE Estimation of Low Baseline Group

Note: Treated and controlled observations and corresponding means in pre- and post-intervention periods in Low expenditure category of the naïve model

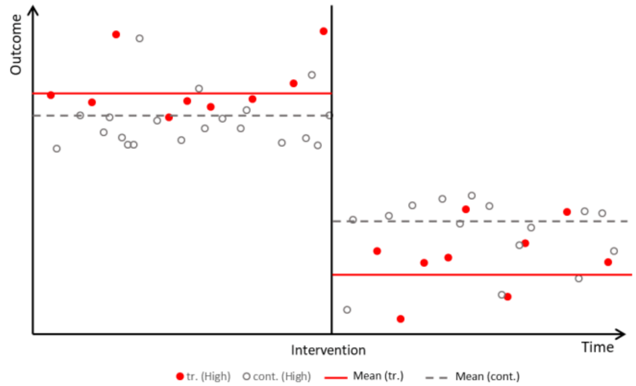

Figure 2-4. Our Modified HTFE Estimation of High Baseline Group

Note: Treated and controlled observations and corresponding means in pre- and post-intervention periods in High expenditure category of the modified model

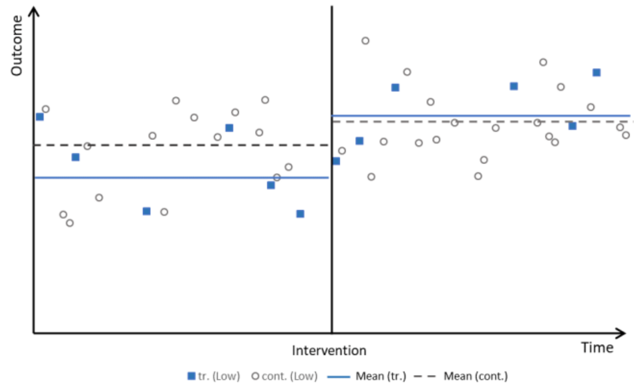

Figure 2-5. Our Modified HTFE Estimation of Low Baseline Group

Note: Treated and controlled observations and corresponding means in pre- and post-intervention periods in Low expenditure category of the modified

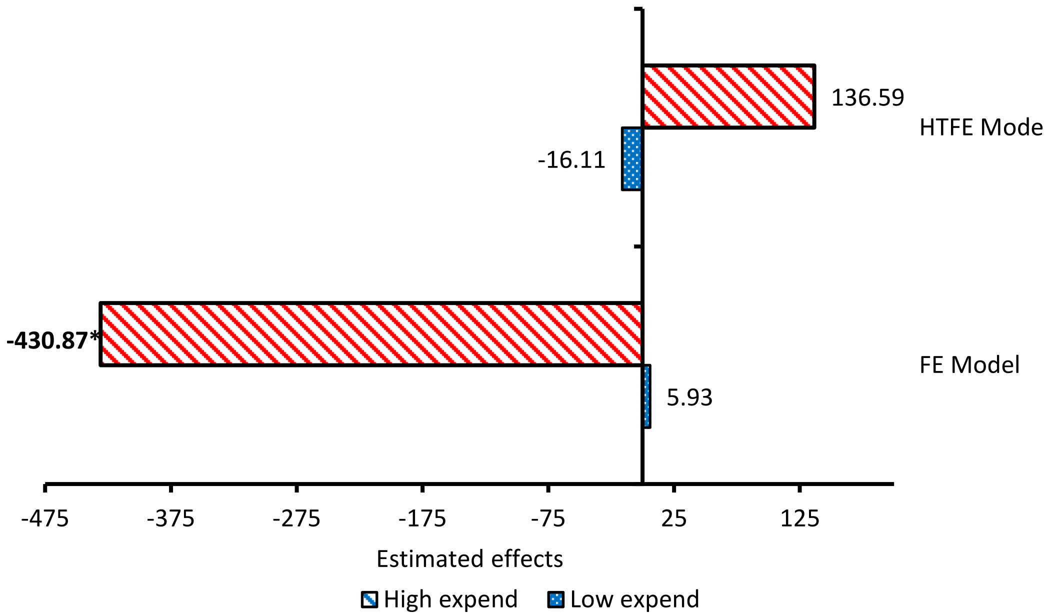

Figure 2-6. The effect of CSA participation
Note: The effect of CSA participation on diet-related medical expenditures by model, baseline expenditure categories, and year of enrollment in CSA.

2.7 Tables

Table 2-1. Summary Statistics

Variable	Definition	Average	SD	Range	Obs.
$gender$	=1 if male; 0 otherwise	0.27	0.44	0-1	27,948
dob	Year of birth	1974.80	12.04	1939-1997	27,948
$diet\_claims\_t$	Number of diet-related medical claims in period t	0.27	0.90	0-18	27,948
$diet\_expend\_t$	Diet-related medical expenditures ($) in period t	157.40	1114.89	0-32,506.4	27,948
$avg\_b\_diet\_expend$	Average diet-related medical expenditure over the baseline periods 1 to 3.				
hi_expend	Diet-related medical expenditures of participants with baseline expenditures of higher than the average	1612.28	3623.17	0-32,506.4	1,110
lo_expend	Diet-related medical expenditures of participants with baseline expenditures of lower than the average	97.22	812.43	0-32,077.2	26,838

Table 2-2. Medical Expenditures by CSA Participation and Billing Periods

Time periods		Baseline			Intervention		
		(i)	**(ii)**	**(iii)**	**(iv)**	**(v)**	**(vi)**
		Jan-Jun 2014	Jul-Dec 2014	Jan-Jun 2015	Jul-Dec 2015	Jan-Jun 2016	Jul-Dec 2016
CSA Non-Participants [n = 4,448]	lo_expend	29.21	25.21	41.99	137.03	186.49	157.12
		137.97	*136.30*	*178.71*	*1073.90*	*1280.33*	*1068.05*
	hi_expend	2553.97	1329.25	2313.09	985	1322.97	1245.82
		4786.30	*2928.24*	*4347.58*	*2964.32*	*3204.08*	*3127.89*
CSA Participants [n = 210]	lo_expend	57.82	34.67	82.70	211.50	188.22	149.79
		183.87	*173.02*	*241.35*	*1095.87*	*920.41*	*504.09*
	hi_expend	1816.49	2191.48	2229.29	773.47	1411.49	579.13
		3085.90	*3374.75*	*4629.60*	*716.29*	*4104.98*	*1044.21*

Notes: The average diet-related medical expenditures by CSA participation and billing period are reported. The number of observations is reported in square brackets. The standard deviations of the subsample means are italicized and reported in parentheses beneath each subsample mean.

Table 2-3. Evidence of Mean Reversion

Dependent Variable: Diet-related medical expenditures ($)	(1) FE	(2) HTFE
lo_expend	5.93	-16.11
	(55.35)	(55.22)
hi_expend	-430.87***	136.59
	(172.46)	(180.90)
Controls	YES	YES
Individual FE	YES	YES
Time FE	YES	NO
Time by Baseline Expenditure FE	NO	YES
Observations	27,948	27,948

Note: Standard deviations are in parentheses. Triple asterisks (***) indicate statistical significance at the 1% level. Control variables include gender, age, and number of medical claims.

Table 2-4. Evidence of Mean Reversion (Placebo Results)

Dependent Variable: Diet-related medical expenditures ($)	(1) FE Model	(2) HTFE Model
lo_expend	13.50	-7.78
	(26.35)	(25.73)
hi_expend	-325.38***	-1.41
	(62.23)	(63.27)
Controls	YES	YES
Individual FE	YES	YES
Time FE	YES	NO
Time by Baseline Expenditure FE	NO	YES
Observations (from 2015)	23,856	23,856

Note: Standard deviations are in parentheses. Triple asterisks (***) indicate statistical significance at the 1% level. Control variables include gender, age, and number of medical claims.

Table 2-5. Matching Results

A) Balance Match Results

Aggregate Baseline Diet-Related Medical Expenditure

Balancing Variables	Difference Value Between Control and Treatment Participants: Before Match	After Match
$gender$	0.01 (01.38)	-0.00 (1.06)
dob	-4.30 (40.32)***	-0.20 (2.19)
$diet\_claims\_1$	0.23 (20.46)***	0.05 (4.18)*
$diet\_claims\_2$	0.26 (18.12)***	0.06 (4.29)*
$diet\_claims\_3$	0.22 (20.33)***	-0.04 (3.51)
$diet\_expend\_1$	93.51 (08.89)	35.34 (3.60)
$diet\_expend\_2$	155.94 (13.21)*	27.10 (2.30)
$diet\_expend\_3$	150.16 (09.94)	15.97 (1.06)

B) Results of Estimated Average Treatment Effects on Treated

Outcome Variable ($)	Estimated ATTs
$diet\_expend\_4$	34.30 (95.67)
$diet\_expend\_5$	-67.36 (136.33)
$diet\_expend\_6$	-87.51 (66.08)
avg_diet_expend	-40.19 (61.62)

Note: Single, double, and triple asterisks (*, **, ***) indicate statistical significance at the 10%, 5%, and 1% levels. Standard errors are in the parentheses.

CHAPTER 3. ARE THERE RACIAL DISPARITIES OF DIABETES CONTROL AMONG SNAP PARTICIPANTS?

3.1 INTRODUCTION

Over the past three decades there has been a continuous increase in the prevalence of diabetes and related mortality among US adults. More than 10% of the US population had diabetes in 2018 (CDC, 2021), with certain ethnic and racial minorities experiencing higher rates of prevalence (CDC, 2015). Food insecurity has been linked to increased rates of diabetes prevalence (Seligman et al., 2010). Supplemental Nutrition Assistance Program (SNAP) is designed to combat food insecurity in the US, but its effectiveness in managing diabetes has yet to be studied. This study seeks to examine the potential correlation between SNAP participation and diabetes management, paying particular attention to any racial disparities in diabetes management outcomes.

Previous research demonstrated that certain racial and ethnic groups may have a lower level of stability in maintaining good health compared to others. This problem is more pronounced for chronic diseases (Pan et al., 2015; Franckle et al., 2014; Lane et al., 2021). Especially, the rate of diagnosed diabetes is not evenly distributed among populations with different racial and ethnic backgrounds (CDC, 2015). The Diabetes Report Card (2021) states that certain racial and ethnic minority groups, such as American Indian or Alaska Native adults, Hispanics, and non-Hispanic Blacks, are more prone to diagnosed diabetes compared to non-Hispanic whites in the US.

The significant racial disparity in diabetes is causally linked, directly or indirectly, to diet and dietary habits (Grummon & Taillie, 2018; de Koning, Shannon, 2009; Lopez and Rodgers, 2002; Denaei et al., 2009; Malik et al., 2010). Diet contributes to maintaining low glucose (blood sugar) levels and is one of the cornerstones of diabetes management. In line with the racial disparity in the prevalence of diabetes, studies have shown that lower-income (Dray-Spira et al., 2008) and food insecure populations (Seligman et al., 2010), have higher prevalence of diabetes. Low-income populations are more susceptible to disparities in nutrition and diet, which can lead to racial and ethnic disparities in diabetes (Grummon & Taillie, 2018; Walker et al., 2010).

Among the public levers available for lowering these ethnic/racial disparities in people's diets, the Supplemental Nutrition Assistance Program (SNAP) is the largest nutrition assistance program in the U.S. and served almost 40 million Americans in 2020 (Andreyeva et al., 2015; Bovell-Ammon et al., 2019; Grummon & Taillie, 2017; Leung et al., 2017; USDA, 2022). This in-kind program provides benefits once per month through an electronic debit card to qualified households to purchase food (Arteaga et al., 2018; Bovell-Ammon et al., 2019; Kuhn, 2018; Wilde & Ranney, 2000). As the primary tool to improve food security and diet quality in America for the low-income households (Andreyeva et al., 2015; Arteaga et al., 2018; Bovell-Ammon et al., 2019; Grummon & Taillie, 2017, 2018), SNAP participation is linked to better health outcomes in cases such as healthier newborn babies (Almond et al., 2011), reduced risk of developmental delays (Bovell-Ammon et al., 2019), and less hospitalization, underweight, ER visits (Arteaga et al., 2018).

Among the low-income and food insecure populations who participate in SNAP, minorities benefit from SNAP's reach to a large extent (Grummon & Taillie, 2018). In 2015, roughly half of the SNAP caseload were racial and ethnic minorities, such that almost one-third were African American and one-tenth were Hispanic (Arteaga et al., 2018). Therefore, changes to the SNAP are likely to be instrumental in addressing the racial disparity in the prevalence and management of diabetes. The controlling factors for diabetes are blood sugar level its fluctuations. SNAP participation can be a contributor to both factors. First, while SNAP is positively correlated with the majority of health outcomes, studies also identified a negative linkage of participation to dietary related outcomes such as obesity (Leung et al., 2012A; B) and diabetes (Andreyeva et al.,2012) due to the above-recommended consumption of sugar- and calorie-dense food. Such linkage could also vary based on the racial and ethnic backgrounds of the respondents. Second, maintaining a consistent glucose level is one of the cornerstones of diabetes management (CDC, 2021). However, studies have shown that SNAP participants follow a cyclical pattern in food consumption and dietary habits (Kuhn, 2018; Wilde & Ranney, 2000; Arteaga et al., 2018) where relatively more calories are consumed during the early weeks of the SNAP month. Such cyclical character of SNAP timing might complicate diabetes control as intra-monthly changes in food consumption are likely to cause fluctuation in SNAP participants' diabetes control.

However, to the best of our knowledge, the ethnic-specific behavior of SNAP participants in diabetes management has not been addressed to date. To address these gaps in the literature, I aimed to estimate the relationship between participation in the SNAP program and diabetes control as well as the association between the number of days since SNAP benefit receipt and diabetes control specific to race and ethnic groups. Specifically, I investigate if there is racial disparity in the management of diabetes among SNAP participants and explore the extent to which cyclical food hardship due to

SNAP payment schedules may complicate glucose control among SNAP participants of different racial groups and ethnic backgrounds.

The remainder of the paper is structured as follows. The next section lays out the methodology used to analyze the racial disparities in SNAP participation and SNAP timing effects on diabetes control. In Section III, I introduced the data as well as the variables used in this paper in detail. The findings of the analysis are reported in Section IV followed by the discussion about the results in Section V. Ultimately, in Section VI, I noted the concluding remarks of the paper.

3.2 METHODOLOGY

I examine the SNAP participation status for each racial and ethnic group among SNAP participants and income-eligible non-participants by allowing the variable $SNAP_i$ to vary over racial and ethnic groups. Moreover, to identify the racial/ethnic disparities in the monthly cycles of diabetes control, I assessed the number of weeks since the participant received SNAP benefits over each racial and ethnic background among SNAP participants and SNAP income-eligible non-participants by allowing the equation to vary over racial and ethnic groups.

In particular, I designed the following framework, to explore the effectiveness of SNAP participation in improving diabetes control among racial and ethnic backgrounds via equation 1 as follow.

$$Y_i = \beta \cdot SNAP_i \times race_i + \alpha X_i + \varepsilon_i \tag{1}$$

where Y_i is the outcome variable indicating the diabetes level of income-eligible SNAP participant i, $SNAP_i$ is the participation status, $race_i$ is the race indicator for the ethnic background of participant i, X_i is a vector of control variables thought to influence the diabetes level, and ε_i is the unobserved factor influencing the diabetes level for participant i.

As stated earlier, regulating fluctuation of glucose levels and diabetes is important. To capture the impact of SNAP's payment timing on these fluctuations, I consider a weekly dynamic model among racial minorities in equation 2.

$$Y_{ij} = \beta_j week_{ij} + \alpha_j X_{ij} + \varepsilon_{ij} \quad \forall j = White, Hispanic, Black, Other \quad (2)$$

Here Y_{ij} is the outcome variable indicating the glucose level of income-eligible SNAP participant i of racial group j, $week_{ij}$ is the number of weeks since SNAP participant i of ethnic group j received last SNAP benefits, X_{ij} is a vector of control variables, ε_{ij} is the unobserved factor influencing the diabetes level, and j is race consisting of White, Hispanic, Black, and other race.

Models (1) and (2) were estimated using pooled ordinary least squares with robust standard errors controlling for socio-economic features, i.e., the participant's gender, income level, education level, and age. The key exposure variables were $SNAP$ and $week$. For the primary dependent variable, I use values from A1c tests[1] which

[1] Also known as Glycohemoglobin or glycosylated hemoglobin

measure average blood sugar levels[2]. I estimated two specifications for each equation above, one without any control variables and the other with all socio-economic control variables categorized over diabetic and non-diabetic SNAP income-eligible participants.

3.3 DATA

Data for this study came from National Health and Nutrition Examination Survey (NHANES) dataset. The NHANES combines respondent interviews with detailed physical examination and laboratory test data for a representative sample from the US population. Notably, the NHANES Laboratory Data includes measures of glucose control (e.g., glycohemoglobin, or A1c, plasma fasting glucose, cholesterol, and measurement of insulin). The demographic dataset includes detailed socio-demographic backgrounds (e.g., gender, age, race, education, marital status, household size, and income) for respondents of age 12 years and older. The dietary dataset consists of the respondents' food intake (e.g., energy, protein, carbohydrates, dietary fiber, and fat). As the indicator for time since the last receipt of SNAP benefit, the NHANES questionnaire asks respondents how many days last since the household received SNAP benefits.

[2] A1c measures the blood sugar level over the past three months and usually ranges between 5 and 14% (NHANES). A below 6.5% of A1c is generally considered the normal blood sugar level, while the American Diabetes Association (ADA) recommended A1c ≥ 6.5% as a diagnostic criterion for diabetes (Radin, 2014). In addition to our primary outcome variable (A1c), I utilized fasting glucose, plasma glucose, and insulin to check the robustness of our results. I also re-estimated model (2) using different time intervals, i.e., three-day and ten-day time intervals, instead of the primary SNAP timing outcome variable ($week$), to check the robustness of our results.

Together, six waves of datasets, i.e., 2007-2008, 2009-2010, to 2017-2018, were used in this analysis. To prevent selection into the sample bias, I restricted our sample to income-eligible individuals to receive SNAP benefits at the study date. I dropped all nonqualified SNAP participants whose household-relative income levels were more than the eligibility level income. For the race identifier, I consider all Mexican-American and other Hispanic individuals as Hispanic, Non-Hispanic Black as black, Non-Hispanic White as white, and non-Hispanic other races, including multi-racial as other races. I considered individuals whose race is defined as black as the reference ethnicity throughout our analysis.

3.3.1 SNAP Participation and Eligibility

NHANES dataset categorized the households' annual income from less than $5,000 to more than $100,000 in 15 categories. In line with previous literature (e.g., Grummon & Taillie, 2018 & 2017), I limit our sample to the federal cutoff of SNAP-eligible households to maximize the comparability of our study. Households were considered income-eligible for SNAP if their reported total household income was less than or equal to 130% of the Federal Poverty Level (FPL), which is the gross-income cutoff for SNAP eligibility at the federal level (USDA Food and Nutrition Service, 2021).

NHANES questionnaire provides information on their household's participation in SNAP by responding to the questions about whether they are currently receiving SNAP benefits. The interviewees could indicate whether they were current, past, or never participants. Out of 3,504 observations that met the reporting requirements and had a household size of 5 members, 50.51% of observations (n = 1770) provided a response to the item about SNAP participation and were included in the sample. Observations without data on SNAP participation because of nonresponse (n = 46,775; 78.2% of the sample) were excluded from the main analyses. Additionally, the NHANES interviewees also provided information on the number of days since their last receipt of SNAP benefits payment.

I classified current SNAP participants if respondents indicated that they were current SNAP recipients and received their last benefit during the past four weeks from the interview date and SNAP income-eligible non-participants if they noted that their income was less than or equal to 130% of the FPL and not identified as current SNAP participants.

3.3.2 Outcome Variable

The main outcome of the analysis was glycohemoglobin or glycosylated hemoglobin (denoted as A1c). The A1c test measures the weighted average plasma glucose level over the past two to three months and typically ranges between 5% and 14% (NHANES). In particular, the most recent levels have a considerably greater influence on A1c test values than levels from more distant periods (Radin, 2014; Tahara & Shima, 1995). This implies that recent dietary intakes influence A1c results to extent than older dietary intakes. In addition, if there is a variation in A1c levels, then it is probable that the actual difference in plasma glucose levels would be more prominent. This is a crucial note to consider in interpreting the results since A1c underestimates the actual plasma glucose level. Following CDC (2018), I classified the individuals as diabetic if their A1c level was 6.5% or higher.

As a robustness check, I replaced A1c with four other measures of blood sugar levels: fasting glucose, two-hour glucose level (mg/dL), plasma glucose (mg/dL), and insulin level (uU/mL). The fasting glucose index is a measure that checks the fasting blood sugar levels. A two-hour glucose level (mg/dL) is reported by the oral glucose tolerance test (OGTT) and checks the blood sugar levels before and two hours after drinking a special sweet drink showing how one's body processes sugar. I then re-estimated the models having these outcome variables substituted in the equations.

I estimate our models using pooled ordinary least squares over diabetic and non-diabetic SNAP participants and income-eligible non-participants. Of 38,516 observations that met the diabetes definition, 10.22% of observations (n = 3,937) were diagnosed diabetic. Observations with missing data on A1c were excluded from the analysis.

3.4 RESULTS AND DISCUSSION

A summary of descriptive statistics is reported in Table 3-1. Of the 4,157 SNAP income-qualified observations, 476 were categorized as diabetic. On average, among SNAP income-eligible respondents, A1c was 1.56 times greater in those with diabetes (8.43%) than non-diabetic respondents (5.41%). Diabetic SNAP income-eligible households were placed, on average, in older age (58 versus 36 years old) and lower-income categories (3.31 versus 3.84). Of the 4,157 SNAP income-qualified observations, 3,865 or 93% were current SNAP participants. The diabetes rate was highest among Hispanic households (13.2%), followed by Black households (10.7%) and white households (9.5%). Hispanic households were more dispersed in average A1c between diabetic and non-diabetic SNAP income-eligible households (1.59 times greater), followed by White households (1.55 times greater) and Black households (1.54 times greater). It is worth mentioning that Black households had the highest standard deviations in the A1c index (2.39 for diabetic and 0.43 for non-diabetic), followed by Hispanic households (2.18 for diabetic and 0.38 for non-diabetic) and White households (1.86 for diabetic and 0.38 for non-diabetic).

Figure 3-1 shows the pattern of the findings of model (1) in estimating the racial disparities in diabetes control between Black and white households. Across most outcomes, there are statistically significant disparities favoring white households over black households. For A1c, these positive differences mean black households have higher blood sugar levels than whites. These disparities are nearly always meaningful among non-diabetic participants. For some outcomes, i.e., fasting glucose, non-diabetic black households showed advantages over non-diabetic whites. Although these advantages persisted among diabetic households in terms of fasting glucose and insulin level, the differences were not statistically significant.

Our sample reveals a number of differences in racial-specific characteristics concerning the diabetic status and food intakes between black and white SNAP income-eligible households. As depicted in Figure 3-1, among non-diabetic participants, black households had meaningfully higher A1c levels than white households ($p < 0.05$). This disparity persisted among diabetic participants ($p < 0.05$). Further, several disparities between black and white households emerged among non-diabetic participants that did not exist among the participants with diabetes. For example, while there were no underlying black-white disparities among diabetic participants for fasting glucose and insulin levels, notable disparities emerged among non-diabetic participants. Compared with non-diabetic white participants, non-diabetic black participants had significantly lower fasting glucose levels and significantly higher insulin levels (all $p < 0.05$).

There are some underlying reasons why fasting glucose can be lower than A1c, e.g., differences in glucose metabolism[3]. A1c measures the average blood glucose levels over the past 2-3 months, while fasting glucose measures the amount of glucose in the blood at a single point in time. It's possible that person B has a faster glucose metabolism than person A, which causes their body to clear glucose from the blood more quickly, thereby leading to a lower fasting glucose level. However, over time, the faster metabolism may cause more glucose to be converted into glycated hemoglobin (A1c), resulting in a higher A1c level.

The pattern of results stayed almost similar for Hispanic households. Figure 3-2 graphically summarizes the racial disparities in diabetes status between Hispanic and white households. White households showed advantages over Hispanics in both non-

[3] Other potential underlying reasons include differences in insulin sensitivity and health conditions. Insulin is a hormone that regulates glucose levels in the blood. People with higher insulin sensitivity require less insulin to control their blood glucose levels and vice versa. If person A has lower insulin sensitivity than person B, they may require more insulin to maintain healthy blood glucose levels, leading to a higher A1c level but not necessarily a higher fasting glucose level. Moreover, certain health conditions can affect the formation of glycated hemoglobin (A1c) independently of blood glucose levels. For instance, people with anemia or hemolytic disorders may have lower A1c levels than expected despite elevated blood glucose levels. In such cases, fasting glucose levels may not accurately reflect a person's long-term blood glucose control.

diabetic and diabetic SNAP income-eligible participants. For instance, A1c was higher in diabetic and non-diabetic Hispanic households than whites ($p < 0.05$). Hispanic households, non-diabetic and diabetic ones, were also worse off than whites in other diabetes indices, i.e., fasting glucose and insulin levels. However, fasting glucose was not significantly higher among non-diabetic Hispanic households than white. Also, the difference between non-diabetic Hispanic and non-diabetic white households in insulin levels was not meaningful.

3.4.1 Racial Disparities in SNAP Participation Effect on Diabetes Control

The association between SNAP participation[4] and the participants' diabetes level across diabetic and non-diabetic subsamples by race and ethnicity is reported in Table 3-2. Columns 1, 3, 5, and 7 report the model estimations from the pooled ordinary least squares unadjusted for socio-economic features as checkpoint estimates and the rest of the columns report the model estimations adjusted for socio-economic features. As

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[4] To further check the potential self-selection issue of SNAP participants (i.e., endogeneity issue, where participation in SNAP affects the participants' blood sugar while diabetic individuals are more likely to register for SNAP benefits), I used a Two-Stages Least Squares model and tested whether the exogenous variations in the SNAP participation variable, i.e., the probability that each individual participate in the SNAP program, significantly affect the A1c level of the participants. Further, I used the F-statistic to assess whether such regression exists. The findings show a non-significant effect of the probability of participating in SNAP on the corresponding participant's A1c level. Moreover, the F-statistics is non-significant, signifying that such a relationship does not exist. I supported our results using a Durbin-Wu-Hausman test for endogeneity, following Davidson & MacKinnon (1993). The results are reported in the appendix.

reported in Table 3-2, all of the estimated effects of SNAP participation on A1c were insignificant except for model in column (5), signaling that SNAP participation weakly affected A1c levels among SNAP participants. This suggests that SNAP program may have a very small impact on overall blood sugar control, regardless of the race.

In contrast, most of the estimated coefficients of race and ethnic were found to be statistically significant. This suggests that among SNAP income-eligible households, non-hispanic black people and Hispanic people have significantly different A1c levels than non-hispanic white people. Among non-diabetic SNAP income-eligible households, non-hispanic black households have the proportionately highest A1c levels compared to non-hispanic white households, while Hispanic households follow closely behind. A similar pattern also exists among diabetic SNAP income-eligible households where non-hispanic black people have an estimated coefficient of -1.05 while the estimated coefficient is not statistically significantly different than zero for Hispanic people.

Four of eight estimated coefficients of the interaction between race and SNAP participation were statistically significant. This suggests that among non-diabetic SNAP income-eligible households, SNAP participation has benefited Hispanic people in lowering their A1c level, while, among diabetic SNAP income-eligible households, SNAP participation has inversely affected non-hispanic black people's A1c level. These findings suggest that non-Hispanic black people with diabetes may experience a worsening of blood sugar levels after receiving SNAP benefits. This may be due to the fact that people may not use their benefits to purchase healthy foods such as sugary beverages that can help lower blood sugar levels. Instead, they may purchase foods with high levels of added sugar, which can increase blood sugar levels. This results is in line with Bleich et al. (2013) where they found that SNAP eligible adults in the U.S. consume more sugary beverages than SNAP ineligible adults.

Our findings on the SNAP participation effects on its participants' diabetes control with a focus on racial and ethnic disparities highlight that diabetic and nondiabetic White households who were income-eligible SNAP participants consistently have the least A1c level, regardless of diabetes status. This finding is consistent with that of (Gaskin et al., 2014; LaVeist et al., 2009; Lipman et al., 2021; Rosenstock et al., 2014). Further, our study stands out in the literature in a sense that it uniquely assesses the racial disparities in diabetes control among SNAP participants by their diabetes status. Our findings suggest that among diabetic and non-diabetic participants, non-hispanic Black households have the highest A1c levels, followed by Hispanic households. Our findings also suggest that SNAP food policy had a significant impact in lowering long-run blood sugar level among non-diabetic Hispanic people while it did not help diabetic non-hispanic black people in managing their diabetes status. All in all, there are similarities between the findings of this study and those described by Grummon & Taillie (2018) where a significant black-white disparity has been found among SNAP participants in consuming sweetener-oriented products.

3.4.2 Racial Disparities in SNAP Timing Effect on Diabetes Control

Figure 3-3 shows that among non-diabetic SNAP income-eligible participants, no significant cyclical component is observed over racial groups (Average glucose levels range between 5.3% to 5.5% among all races). Among the diabetic respondents, I do not see any cycles emerge among white SNAP participants; however, significant blood sugar fluctuations are observed among black and hispanic SNAP participants. Visually inspecting, after a few days of receiving the SNAP benefit among black and hispanic households, their A1c levels get increased and this increment in their A1c level lasts for two weeks, which is in line with (Valluri et al., 2021). Afterward, their blood sugar levels start to fall until a few days after they received their next month's SNAP benefits.

In the pooled ordinary least squares model (2), I estimated the association between SNAP monthly cycles and diabetes management, focusing on whether this association differed by race and ethnicity. From column (A) in Table 3-3, non-diabetic SNAP income-eligible participants did not experienced statistically meaningful fluctuations in their A1c levels. This table also reveals that the association between SNAP cycles and diabetes control among diabetic black participants is statistically significant. Using the last week of the proceeding month as a reference, i.e., week 1, Black households experienced a meaningful jump in their A1c levels in weeks 3 and 4. Although Hispanic and white SNAP participants experience a similar pattern in increasing their A1c levels as they went beyond the first half of the month, no statistically significant hikes in the A1c levels were observed. These findings reveal that the diabetes control among diabetic black households who were SNAP income-eligible is significantly different from White and Hispanic groups.

On the SNAP-timing analysis, the racial disparities in SNAP monthly-cycle effect on A1c levels over non-diabetic and diabetic SNAP participants are depicted in Figure 3-3. This figure consists of two rows of triple plots depicting A1c levels and 95% confidence intervals under the days since SNAP participants received the last SNAP benefits. Figure 3-3 visually illuminates the pattern of the results in highlighting important heterogeneity in SNAP timing effects by race and ethnic background. When one treats A1c levels homogenously across all ethnicities, false/biased results may be obtained. Additionally, if one takes the average value of A1c and does not distinguish the A1c levels by daily records, even when racial heterogeneity is accounted for, they may not assess how different racial groups can respond differently to diabetes management.

Our findings on the racial disparities in the SNAP-timing effect on diabetes control suggest that the SNAP households' food purchase decreases in late benefit-month, resulting in more unstable A1c levels. These results reflect those of Valluri et al. (2021) who also found that increased fruit and vegetable purchases were only seen in the first two weeks after receiving benefits. This results is also in line with the findings of Young et al. (2022) who found that the timing of SNAP benefit disbursement may have an impact on the health outcomes of individuals who rely on this program for food assistance. This result also accords with our earlier observations from Figure 3-3. Moreover, in line with Dorfman et al. (2019) and Valluri et al. (2021), our findings suggest that the SNAP households' food purchases decreases in late benefit month, resulting in more unstable A1c levels. Our findings suggest that SNAP benefits effectively lower diabetes levels among diabetic black households for half of a month.

3.5 CONCLUSION

This paper studied how diabetes control is related to the Supplemental Nutrition Assistance Program (SNAP) participation with a focus on how this association differed across different races and ethnic backgrounds. This analysis, in addition, explored how diabetic control is related to the SNAP timing, i.e., the time since the SNAP payment benefits are received, and how this relation is defined across different races and ethnic backgrounds.

Our findings indicated an association between SNAP participation and A1c in diabetic SNAP participants in which the magnitude of the relationship is different across race and ethnic groups. Further, A1c was associated with SNAP timing with different volumes over the weeks when the benefit was received for black participants. Understanding how the SNAP cycle influences glucose management will enable the SNAP administration and policymakers to make any necessary changes to improve public health. To neutralize the SNAP-cycle effect, the policymakers should reevaluate the frequency and the amount of the SNAP benefits for the most susceptible population (diabetic black households).

3.6 FIGURES

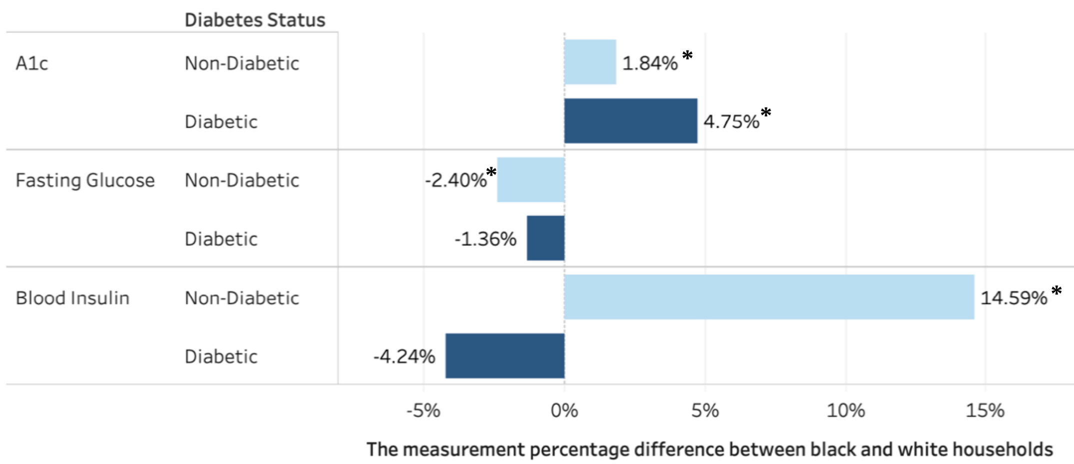

Figure 3-1. Diabetes Measurements in black vs. white
Note: Differences in the averages of elite measurements and indices of black vs. white SNAP income-eligible households

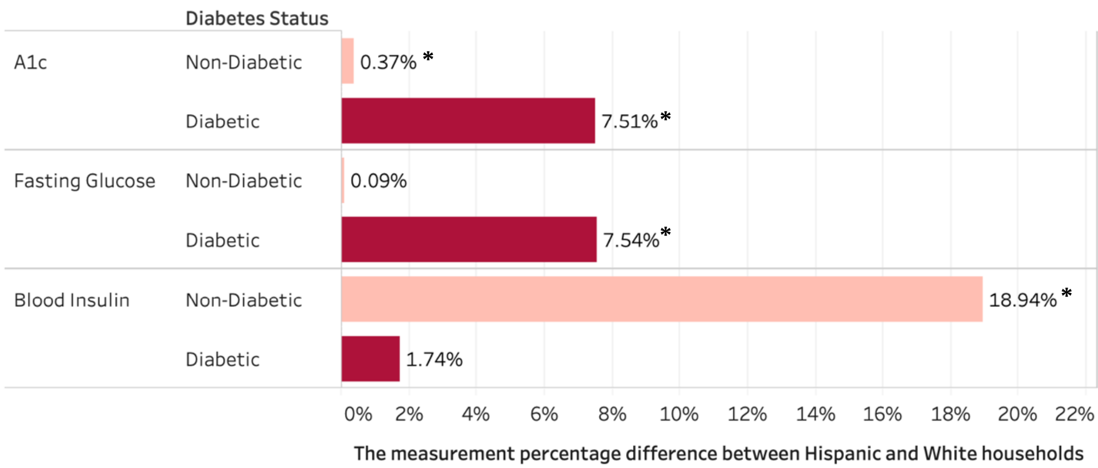

Figure 3-2. Diabetes Measurements in hispanic vs. white

Differences in the averages of elite measurements and indices of hispanic vs. white households

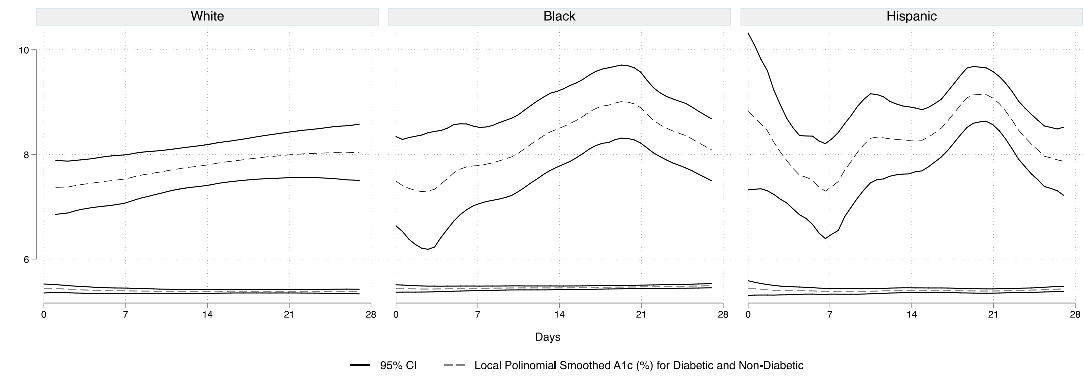

Figure 3-3. A1c level of Racial Minorities

Note: A1c (%) over the number of days since receipt of SNAP benefits among diabetic (top row plots) and non-diabetic (bottom row plots) SNAP income-eligible participants.

3.7 TABLES

Table 3-1. Variable Definitions and Summary Statistics

Variable	**Definition**	**Non-Diabetic Sub-Sample (N = 4,157)**	**Diabetic Sub-Sample (N = 476)**	**Difference (P-Value)**
(A)				
A1c	2-months average Alc level (%)	5.41 (0.40)	8.43 (2.15)	
Black	1 if non-hispanic black household	0.33 (0.47)	0.31 (0.46)	
Hispanic	1 if Hispanic household	0.31 (0.46)	0.36 (0.48)	
White	1 if non-hispanic white household	0.29 (0.45)	0.24 (0.43)	
SNAP	Income-eligible SNAP participants	0.93 (0.26)	0.95 (0.21)	
Gender	1 if male, 0 otherwise	0.56 (0.50)	0.59 (0.49)	
Age	(Years)	35.92 (19.21)	58.14 (13.93)	
Income	Income level (categorical variable)	3.83 (1.68)	3.34 (1.52)	
(B) **A1c Level (%)**				
SNAP				
Participants	A1c for SNAP participants	5.41 (0.40)	8.43 (2.18)	3.02* (0.00)
Non-Participants	A1c for SNAP non-participants	5.40 (0.38)	8.38 (1.38)	2.98* (0.00)
Race/Ethnicity				
Black	A1c for non-hispanic Black households	5.45 (0.43)	8.49 (2.39)	3.04* (0.00)
Hispanic	A1c for Hispanic households	5.40 (0.39)	8.57 (2.14)	3.17* (0.00)
White	A1c for non-hispanic White households	5.36 (0.38)	8.25 (1.81)	2.89* (0.00)
Gender				
Male	A1c of male	5.41 (0.40)	8.41 (2.03)	3.00* (0.00)
Female	A1c of female	5.41 (0.40)	8.45 (2.23)	3.04* (0.00)

Table 3-2 SNAP Participation Effects on Diabetes by Race

Effects on A1c	(A) Non-diabetic		(B) Diabetic		(C) Non-diabetic		(D) Diabetic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$SNAP$	.03	-.01	-.22	-.15	.09	.03	-.86	-.40
$ethnicity$ (reference: $white$)								
$black$	.11***	.14***	.32	.38	.17**	.18***	-1.41*	-.97*
$hispanic$	.04*	.08***	.57**	.69***	.18***	.18***	.13	.99
$SNAP \times ethnicity$ (reference: $white$)								
$black$	-	-	-	-	-.06	-.04	1.80*	1.39**
$hispanic$	-	-	-	-	-.15***	-.10*	.46	-.31
Constant	5.42***	5.03***	8.47***	9.45***	5.26***	4.99***	9.07***	9.70***
Interactions	No	No	No	No	Yes	Yes	Yes	Yes
Control	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4,157	4,039	476	457	4,157	4,039	476	457
R-sq	.01	.16	.01	.09	.02	.16	.02	.10
F	5.93	39.38	1.67	3.02	4.14	33.31	19.72	12.16

Notes: The results of the association between participation in the supplemental nutrition assistance program (SNAP) and the participants' diabetes level across diabetic and non-diabetic SNAP-eligible observations by race/ethnicity background are reported. Robust standard errors are in parentheses. The variable reference category (Black) is dropped to avoid perfect collinearity. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% levels.

Table 3-3. SNAP Cycle Effects on Diabetes by Race

Effects on A1c (references group: *week* 1)	(A) Non-diabetic			(B) Diabetic		
	(1) Black	(2) Hispanic	(3) White	(4) Black	(5) Hispanic	(6) White
Week 2	.01	-.00	-.14	.97	-.47	.33
Week 3	-.04	.09	-.10	3.17***	.72	.61
Week 4	.04	.04	-.11	2.51***	.80	.99
Constant	5.16***	5.07***	5.20***	10.15***	9.30***	6.65***
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	851	733	724	107	100	73
R-squared	.14	.18	.16	.39	.30	.38
F-statistic	6.12	17.06	4.96	.54	2.59	7.10

Notes: The results of the association between participation in the supplemental nutrition assistance program (SNAP) and the time since the participants received the benefit across diabetic and non-diabetic SNAP participants by race/ethnicity background are reported. Robust standard errors are in parentheses. The reference category of *week* (week 1) is dropped to avoid perfect collinearity. Week 4 is the most recent week and week 1 is the oldest week since the SNAP benefit is received. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% levels.

CHAPTER 4. AUCTION SELECTION AND SELLING PRICES: THE ROLE OF AUCTION TYPE IN THE FORMATION OF PRICES

4.1 BACKGROUND

With the introduction of online shopping and selling options, the number of selling venues has been increasing over the past decades, therefore, choosing the most appropriate selling venue has been a concern of sellers. Sellers consider a range of factors when selecting the most suitable venue to sell their items, including convenience, intensity of posting-to-selling time, venue-specific costs, and sale prices. It can be of specific interest to the sellers to know that different selling options can lead to differentiated prices, and therefore, it is essential for them to sell their items at the highest price possible. To the best of our knowledge, the net effect of varying selling venues on the items' selling prices has never been studied directly. Our goal is to discover whether sales venues contribute to different sale prices. I will further investigate what factors influence sale venue selection and the extent to which each platform impacts the selling item's price. To address the study objectives, I will use weekly data of used planters sold through a variety of auction channels during 2016 to 2018.

4.1.1 Farm Machinery Markets

Phillips (1958) argues that the structure of the farm machinery markets is determined by three categories of variables: physical factors, which are related to the geographical features of the agricultural market; technological factors, which are generally identified with leading manufacturers; and financial factors. Regional differences can cause farm equipment price differentiation. Most corn-specific machinery sales, for instance, occur in the Midwest region in the U.S., where corn is the major crop (Black, 2007; USDA, 2019). Rural and urban segmentations can also influence choosing different sales venues, and consequently, different prices. Black (2007) argues that it is more common to see sellers in urban areas sell their items through online auctions relative to sellers in rural areas. This may be a result of lower availability of the Internet and lack of Internet expertise in rural areas.

Different state attributes also contribute to choosing the sale venue type. Diekmann et al. (2008) argue that sellers in states with higher valued machinery stock and states with more frequent tractor sales are more likely to sell their equipment through in-person auctions. On the other hand, states where farmers report more frequent uses of the Internet for agricultural marketing purposes are more likely to sell tractors through online auctions. Agricultural equipment's attributes, including equipment's make, quality of their condition, and size, are factors that can affect used agricultural machinery markets and prices.

4.1.2 Farm Machinery Prices

Many studies have investigated the effects different factors have on agricultural machinery sale prices. Most of the previous relevant studies can be classified into four main categories including machine-specific characteristics, overall macro-economy factors, farm-specific economy variables, and sale venues.

Fettig (1963) was the first to study the influence of machine-specific characteristics on sale prices. He found that horsepower and diesel/gasoline engines were responsible for the major price difference between machines. Diekmann et al. (2008)

investigated the auction venue selection and price determinants of tractors under online-offline sale venues and found that larger diesel tractors were more likely to be offered at in-person auctions. More recently, Allison et al. (2022) used a hedonic analysis to analyze the resale price of agricultural planters on the used machinery market and found a significant effect of make, condition, and age on agricultural planters' prices.

Osborne & Saghaian (2013) researched the role of financial and political factors in machinery sales and their overall effect on U.S. agricultural productivity and that interest rates had a negative impact on farm machinery expenditures, while cash receipts relating to commodity prices did not affect agricultural machinery demand and, consequently, their sales. LeBlanc & Hrubovcak (1985) and Fettig (1963) also found that interest rates impact agricultural machinery prices.

Pawlak (2002) investigated the main determinants that led to the historical adjustments of the farm machinery market and found two main reasons for the number of agricultural machines sold in four countries, including France, Germany, Poland, and the U.S. They found that reducing the number of farms and specialization advancements in production accounted for most of the sale volume differences. Osbourne and Saghaian (2013) suggested that machinery expenditures, net farm income, and purchased inputs positively affected farm machinery expenditures.

Diekmann et al. (2008) investigated the determinants of tractor prices sold during online and in-person auctions and the size of the price differentiation between the two auction methods. Their study findings suggested tractor prices from online auctions were lower than in person auctions for comparable machines. Allison (2019) found that sale type can impact the planters’ sale prices.

4.1.3 Auction channels

The existence of different sales venues can result in cause price differentiation. Used planters are generally sold through three venues: online, in-person, and third-party auctions from consignments and dealerships (Nafziger, 1994; De Bruin & Pedersen, 2008; Van Roekel & Coulter, 2011; Allison et al., 2022). I discuss the characteristics of each sale venue in the following sections.

4.1.3.1 Online Auctions

Online auctions are an Internet platform where the seller offers a product or service to the highest bidder. Online auctions for selling used farm equipment began in the early 2000s and gained popularity over time. Online auctions can reduce search costs by giving buyers an easy way to narrow their search, make products and price comparisons more accessible, and expand the geography of their potential selling pool. In addition, online auctions can stay open 24 hours a day and can be readily accessed from any geography, allowing sellers to reach a wider audience, unlike physical auctions (Diekmann et al., 2008; Hilk & Rasmus, 2020; O'Hara & Low, 2020).

Online auctions reduce transportation costs because no transportation is needed for moving the equipment to a central location. Online auctions also have lower operating costs than physical auctions because running physical establishments requires commensurate infrastructure costs. Finally, online auctions offer lower commissions to sellers (Diekmann et al., 2008; Hilk & Rasmus, 2021).

From a buyer's perspective, online sales reduce search and transportation costs, which provides higher satisfaction to the buyers (O'Hara & Low, 2020). In addition, these auctions allow buyers to look for the best deals available in the market. Moreover, it is more likely for an online retailer to offer more discounts and deals than physical auctions due to the lower operational costs of running online establishments (Hilk & Rasmus, 2020).

4.1.3.2 In-Person Auctions

In on-farm auctions, the seller hosts the auction on their farm or property. This is usually done when the seller has a high volume of products that cannot be easily transported. On-farm sellers must engage in marketing to invite prospective buyers onto the property. They must also curate sales by maintaining a clean and inviting property to generate more business (Hannan, 2018).

Although it is more convenient to purchase a product online than in person, purchasing used agricultural machinery through physical stores allow buyers to inspect the machinery and ensure it is in working condition. On-farm auctions are regularly run by farmers and local auctioneers, in which both sellers and buyers can visit the market in person. This type of sales venue is prevalent in areas that support local farmers and is usually characterized by higher priced sales relative to other marketing venues. Auctioneers who arrange and conduct in-person sales are the seller's exclusive agents and charge higher commissions than online platforms (Diekmann et al., 2008).

4.1.3.3 Third-Party Auctions

In consignment auctions, equipment is sold via a third-party seller. This seller receives a fee or commission from the sale in return if their item sells. However, selling through consignment auctions reduces investment risk, as the only cost to the seller is a small fee if the product is sold.

Dealership sales have long been used for the sale of farm equipment. These types of auctions typically take place directly at a dealership. Purchasing from a dealership ensures the machine is in good working order, and they provide the facts upfront for the buyer to make their decision easier. Dealerships also offer a wide variety of equipment and have more extensive stocks of available equipment. Unlike in-person auctions, dealership auctions do not allow buyers to test their equipment prior to the purchase (Briggs, 2018).

This study seeks to understand whether any price differentiation triggered by different selling markets exists, as well as the extent to which each available selling market influences final farm machinery selling prices. Our objectives are to discover the factors that can impact a sellers' decision to choose a specific selling market, to identify the determinants of sale price in each market, and contrast these determinants across different sales venues.

4.2 METHODOLOGY

4.2.1 Estimation Strategies

Our goal is to investigate the extent that auction venues impact sale prices. I also explore what factors could affect the preferred auction channel choice. I used an endogenous switching regression model (ESR) to address the study objectives and further checked the robustness of our results with a Two-Stages Least Squares (TSLS) and a pooled ordinary least square.

4.2.1.1 Market Selection and Price Analysis

I first utilize a switching regression with an endogenous switching model, as explained by Maddala (1990). An Endogenous Switching Regression (ESR) model consists of two key components, a selection equation, and two outcome equations corresponding to each auction choice. There are two choices for the seller to make: the decision to sell implements through sale venue j and the decision to sell their used implements through alternative sale venues. I specify the selection equation corresponding to the decision function for sale venues in equation (1).

$$(1) \qquad V_i = \gamma' \boldsymbol{Z}_i + u_i, \qquad \text{and} \qquad V_i = \begin{cases} 1 \ \ iff \ \ V_i^* > 0 \\ 0 \ \ iff \ \ V_i^* \leq 0 \end{cases},$$

Here V_i^* is the unobservable variable for sale venue selection, V_i is its observable counterpart which takes 1 when the venue of interest is chosen and 0 otherwise. $\boldsymbol{Z}_i$ is a non-stochastic vector of observed equipment-specific characteristics and control variables determining sale venue selection, and u_i denotes random disturbances associated with venue choice.

Sale venue decisions of sellers are assumed to be derived from maximizing the expected utility of selling the implements through sale venue j. A seller chooses venue j over all available alternatives ($\neg j$) if it generates a higher expected utility.

To account for selection bias, I adopt a switching regression model of planters' hedonic pricing with endogenous switching where the sellers of planters face two general regimes (a) to sell their product through venue j and (b) to sell through alternative venues. The regimes in front of each seller introduced by a switching regression model of hedonic pricing with endogenous switching are as follows[5]:

$$P_i = \beta_1' \boldsymbol{X}_i + \varepsilon_{i1}, \qquad if\ V_i = 1\ (sold\ through\ j), \tag{2}$$

$$P_i = \beta_0' \boldsymbol{X}_i + \varepsilon_{i0}, \qquad if\ V_i = 0\ (sold\ through\ \neg j), \tag{3}$$

where P_i is the observed price of planter i, β is the implicit marginal price for each product-specific attribute, $\boldsymbol{X}_i$ represents a vector of exogenous explanatory variables of attributes of the equipment i, and ε_i's are unobserved factors driving the price of machine i sold through venue j.

Since its development, the hedonic demand theory dates from 1974 and has been applied in several industries, specifically agriculture. When applied to agricultural machinery, it has allowed price adjustments and improved price indexes (Allison, 2019). The theory of hedonic prices was formulated to define implicit market prices that economic agents reveal (i.e., sellers and buyers) in a specific market, based on observed

[5] To simplify notation, all j's subscriptions indicating selling venues were dropped from the equations.

prices of differentiated products and the commodity-specific characteristics. The main idea behind hedonic models is that the characteristics of goods generate utility (Rosen, 1974).

Finally, the error terms are assumed to have a trivariate normal distribution with zero mean and non-singular covariance matrix characterized as $(\varepsilon_{ij1}, \varepsilon_{ij0}, u_{ij})' \sim N(0, \mathbf{\Sigma})$ for selling platform j where $\mathbf{\Sigma}$ is the covariance matrix expressed as:

$$\boldsymbol{cov}(\varepsilon_{ij1}, \varepsilon_{ij0}, u_{ij}) = \begin{bmatrix} \sigma_{j1}^2 & \sigma_{j10} & \sigma_{j1u} \\ . & \sigma_{j0}^2 & \sigma_{j0u} \\ . & . & \sigma_{ju}^2 \end{bmatrix}, \tag{4}$$

where σ_u^2 is the variance of the error term in the selection equation (1) and is assumed to be 1, $\sigma_j^2{}'s$ are the variances of the error terms in the hedonic price models in the outcome equations (2) and (3), and σ_{j1u} and σ_{j0u} represent the covariance between $\{\varepsilon_{ij1}, u_{ij}\}$ and $\{\varepsilon_{ij0}, u_{ij}\}$, respectively. Since P_{ij}'s are not observed simultaneously, the covariance between error terms ε_{ij1} and ε_{ij0} is not estimable. The structure of the error terms ε_{ij1} and ε_{ij0} signifies that the expected values of the error terms conditional on the sample selection are nonzero because the error term of the selection equation (1) can be associated with the error terms of the outcome equations (2) and (3).

If $\sigma_{j0u} = \sigma_{j1u} = 0$ then the system of equations (1) through (3) are switching regression models with exogenous switching. If the estimated covariances between error terms in the selection equation and outcome equations are statistically significant, then the corresponding dependent variables of the two model specifications are correlated.

Therefore, the expected values of u_j's conditional on sample selection are non-zero. This leads to sample selectivity bias and provides evidence for endogenous switching (Asfaw & Shiferaw, 2010; Maddala, 1990). Intuitively, the endogenous switching regression model accounts for and corrects for potential correlation between the model's choice stage and payoff stage. It could be that the choice stage and payoff stage are uncorrelated, which would not hurt the estimates when using a switching regression model.

Under a switching regression model with endogenous switching, the Full-Information Maximum Likelihood (FIML) algorithm provides consistent and asymptotically efficient estimates given proper model specifications (Asfaw & Shiferaw, 2010; Kim et al., 2000). FIML simultaneously fits the binary and continuous parts of the model to yield consistent standard errors (Lokshin & Sajaia, 2004). Moreover, FIML is preferred over other alternative algorithms when there is a high degree of multicollinearity between explanatory variables in the selection and outcome equations (Kim et al., 2000). Given the assumption of the error term distributions, FIML parameter estimates can be obtained from the logarithmic likelihood function

$\ln L\,(\beta_1, \beta_0, \sigma_1, \sigma_0, \rho_{1u}, \rho_{0u}) = \sum_{i=1}^{I} S_i \left[\ln \phi\left(\frac{P_{i1} - \beta_1' X_i}{\sigma_1}\right) - \ln \sigma_1 + \ln \Phi(\eta_{i1})\right] +$

$(1 - S_i)\left[\ln \phi\left(\frac{P_{i0} - \beta_0' X_i}{\sigma_0}\right) - \ln \sigma_0 + \ln \Phi(\eta_{i0})\right]$ for the system of equations, where β_{i1} and β_{i0} are estimated marginal effects of an explanatory variable on the planting machinery prices unconditional on sale venue, ρ_{1u} and ρ_{0u} denote the correlation coefficients between $\{\varepsilon_{i1}, u_i\}$ and $\{\varepsilon_{i0}, u_i\}$, respectively, ϕ and Φ denote the standard normal probability density function and the standard normal cumulative density function, respectively, and $\eta_{ij} = \left[\gamma'\boldsymbol{Z}_i - \frac{\rho_{ju}}{\sigma_j}\left(P_{ij} - \beta_j'\boldsymbol{X}_i\right)\right] / \sqrt{1-\rho_{ju}^2}$ with $j = 1$ and 0. Let the k^{th} variable be identical both in $\boldsymbol{X}_i$ and $\boldsymbol{Z}_i$. The conditional effect on planting implements which were sold through venue j is given by:

$$(5) \qquad \frac{\partial E(P_{i1}|S_i = 1)}{\partial \boldsymbol{X}_{ik}} = \beta_{1k} + \gamma_k \sigma_{1u} \frac{\phi(\gamma' Z_i)}{\Phi(\gamma' Z_i)} \left[\gamma' Z_i + \frac{\phi(\gamma'\boldsymbol{Z}_i)}{\Phi(\gamma'\boldsymbol{Z}_i)}\right].$$

Similarly, the conditional effect on planters which were not sold through venue j is specified by:

$$(6) \qquad \frac{\partial E(P_{i0}|S_i = 0)}{\partial \boldsymbol{X}_{ik}} = \beta_{1k} - \gamma_k \sigma_{0u} \frac{\phi(\gamma'\boldsymbol{Z}_i)}{1-\Phi(\gamma'\boldsymbol{Z}_i)} \left[\gamma' Z_i + \frac{\phi(\gamma'\boldsymbol{Z}_i)}{1-\Phi(\gamma'\boldsymbol{Z}_i)}\right].$$

Equations (5) and (6) breakdown the effect of a change in $\boldsymbol{X}_{ik}$ into two parts. The first part is the direct effect on $P_{i1}(P_{i0})$, or the observed sale price of the planters. The second part captures an indirect effect that appears as a consequence of correlation between the unobservable components of $P_{i1}(P_{i0})$ and S_i, the sale venue selection (Kim et al., 2000).

There are two approaches to analyzing models with multiple choice alternatives, also known as polychotomous-choice models: Models with binary-choice rules and a polychotomous choice model with M categories and one potential outcome in each category (Maddala, 1990). I use the former approach to assess the impact of sale venue selections on used planters' prices.

Having three main sale markets of used planters (i.e., online, in-person, and third-party auctions), I considered one sale market as a base sale venue, then compared the remaining two venues to the baseline venue. In practice, our reference sale venue is the 'online' auction, such that in-person auctions and third-party auctions were compared to online auctions in two separate models. Using this approach, I will also be able to contrast the two remaining sale venues, in-person and third-party auctions, in this case, side by side to the base sale market (i.e., online auctions), due to having their relative coefficients against online venue estimated.

4.2.2 Robustness Checks

4.2.2.1 Two-Stages Least Squares

To investigate whether different selling methods directly cause different sale prices, I used a Two-Stages Least Squares (TSLS) approach. This model takes the form of equations (7) and (8):

$$V_{ij} = \alpha_j' \boldsymbol{X}_{ij} + \varepsilon_{ij} \; j \in \{1,2,3\}, \tag{7}$$

$$P_{ij} = \gamma_j' \hat{V}_{ij} + \beta_j' \boldsymbol{X}'_{ij} + \varepsilon'_{ij} \; j \in \{1,2,3\}, \tag{8}$$

Where P is a continuous outcome variable of the sale price, V is a categorical variable of auction channels with three levels corresponding to each auction venue, $\hat{V}$ is the exogenous counterpart of V, $\boldsymbol{X}$ and $\boldsymbol{X}'$ are vectors of control variables, γ, α, and β are the parameters to be estimated, and ε and ε' are the error terms corresponding to the ith planter sold through venue j.

I used a multinomial logit model in stage 1 to estimate equation (1), then I plugged the exogenous variation in the auction venue obtained from equation (1) into equation (2) to capture the impact on the sale prices. To distinguish each auction venue's impact on the prices, I estimated equation (2) on the corresponding auction venue observations.

4.2.2.2 Heterogeneous Effects of Auction Markets

To further investigate the extent to which each sale venue contributes heterogeneously to the final sale price, I interact the categorical variable of the venue with each control variable. Intuitively, the heterogeneous effects of auction markets spotlight the direction and magnitude of auction venues for each covariate of interest. This heterogeneous impact of auction sale venue on the prices is estimated via equation (9).

$$P_{ij} = \beta_j' \boldsymbol{X}_{ij} \times V_{ij} + \varepsilon_{ij}, j \in \{1,2,3\} \tag{9}$$

where V is a trichotomous variable of auction venue j in which the equipment i is sold through.

4.2.3 Data and Descriptive Statistics

The data used in this article were obtained from the “Auction Price Data” dataset by Machinery Pete. This source compiled a weekly dataset of finalized sales over different locations across the U.S. and from multiple auction companies and machinery dealers for sales occurring from January 2016 to April 2018. There were 2,818 observations in the original dataset. Each observation identifies the auction, machine make, condition, final selling price, sale date, the method of sale, the city and state of sales, and equipment-specific characteristics. The final dataset consists of 847 observations after processing the data.

The price of planters is influenced by financial factors, technology factors, and physical factors. The sale venue variable proxies for financial factors, including dealerships, on-farm, online, and consignment auctions. Equipment-specific features proxy for technological factors which include the make (i.e., Case IH, John Deere, Kinze, White, etc.), condition (fair, good, and excellent), age, the size (i.e., the number of rows attached), and planter row structure. The planters’ sale market region was used as a proxy variable for physical factors. The U.S. was divided into five regions based on ARMS III farm production expenditure regions, defined by USDA NASS in August 2019 (NASS, 2022).

A summary of descriptive statistics is reported in Table **4-1**. The dependent variables include a continuous variable of the final sale price in thousands of dollars and sale venue indicators. In the sample, 21.02% of sales were in online venues, 32.94% of sales were in on-farm auctions, and 46.04% of sales were in third-party auctions, including dealerships and consignments.

I include the variable *class* to reflect the agricultural economy's health in each state. I gathered this variable from the National Agricultural Statistics Service (NASS) of the United States Department of Agriculture (USDA) farm income dataset, referring to categories defined by farm sales plus government payments. It contains every farm's annual income, categorized into ten classifications from "less than $1k" (*k* is used as 'thousands') up to "$1m or more" (m' is used as 'million') and reports the number of operating farms under each economic class. I later aggregated them into two classes:, low and high-income class, corresponding to the threshold of the average farm-related income of the states.

4.3 RESULTS AND DISCUSSION

4.3.1 Endogenous Switching Regression Results

Table 4-2 and Table 4-3 provide the results obtained from evaluating the hedonic price equations (i.e., equations 4 and 5) and venue selection equation (i.e., equation 3). The dependent variable in Table 4-2 is the sale price in a logarithmic form representing the estimated relative sale price. Table 4-3 consists of a binomial variable of sale types that represents the relative propensity to use each venue. The number of observations and measurements of the goodness of fit are reported in the bottom row section of Table 4-2 and Table 4-3.

Table 4-2 shows that equipment-specific characteristics had the most significant impact on the planters' sale prices. Specifically, size, brand, and age were the most influential factors defining the planter shadow prices under all three auction categories. This finding is consistent with that of Diekmann et al. (2008). Additionally, the rest of the results from Table 4-2 goes beyond previous studies, wherein the impacts of planter-specific characteristics on hedonic prices have not been described, signifying weak evidence for the effects condition, row spacing, and region have on shadow prices. It is worth mentioning that, to our knowledge, the present study is the first to examine the impact of planter-specific characteristics on their hedonic price. Finally, in line with our expectations, the relationship between age and the price of the planter was negative. That is, as the age went up, the price of the planter lowered. However, this relationship was not constant and diminished in significance as the relationship continued.

A more detailed inspection of Table 4-2 shows that Kinze planters were sold at a significantly higher price in all three selling venues compared to other makes, followed by John Deere= planters. The sale value on all three selling platforms grows significantly when the planter's size increases. Planters in excellent condition were sold at a significantly higher price compared to fair conditioned planters in online auctions. Planters with more than 30-inch row spacing were sold lower than other planters in online and in-person auctions. This suggests that for planters with row spacing of more than 30 inches, it would be more beneficial to choose third-party auctions to sell those planters. Finally, the planters' age tended to reduce the selling price in online and in-person auctions. However, only online auctions showed a diminishing rate.

Turning to Table 4-3, I can see that the endogenous switching regression model revealed significant effects of region, the sale's timing, and equipment age on choosing a preferred venue. A possible explanation for the region's impact on auction selection is that regions with a lack of auction concentration, more diverse planter characteristics, and more reliable Internet access could favor web-based auctions to sell their items.

Furthermore, the role of time in preferring a particular type of auction is likely related to the fact that sellers take tax season and planting times into account when deciding to sell their planters. Additionally, Table 4-3 reveals weak evidence of the impact of make, condition, size, and row spacing on choosing third-party auctions over alternative sale channels. In contrast, I did not find any evidence that these variables influence the choice of online auctions. The ease of posting items with diverse characteristics on web-based auctions could explain this phenomenon.

Taken together, our findings from Table 4-2 and Table 4-3 highlight generally that equipment-specific attributes had the most significant influence on planter's sale price. However, location and the time of sale were the crucial components of sellers' venue decisions. While most of our results agrees with the conclusions of prior studies, a few do not. For instance, in line with the study of Diekmann et al. (2008), our findings showed the significance of location and time on the propensity to choose online auction over other auction types. On the other hand, contrary to the conclusions from Diekmann et al. (2008), I did not find any evidence that equipment-specific characteristics influence selecting online auctions over alternative channels. It is worth noting that Diekmann et al. (2008) did not cover third-party auctions in their analysis, while our study showed that equipment-specific attributes were influential in choosing third-party auction types over alternative auction channels.

4.3.2 Robustness Checks Results

4.3.2.1 TSLS Results

Table 4-4 and Table 4-5 show the results obtained from estimating equations (1) and (2) via a TSLS model. I found strong evidence that there is an auction venue effect on the item's prices after controlling for the equipment-specific characteristics, physical factors, and financial features. This finding is also consistent with our findings from the existing literature and the endogenous switching regression model, which is demonstrated in the next section.

4.3.2.2 Heterogeneity Results

The results of estimating the heterogeneous impacts of sale venues on final sale prices via equation (9) are presented in Table 4-6 in which panel (A) reports the estimated coefficients of the gross effect of each feature on the log of prices. Panels (B) and (C) in Table 4-6 report the estimated coefficients of the interactions of the auction venues in-person and online on the planters' characteristics, respectively. To some extent, there are some covariates that their impacts on final sale prices are heterogeneous depending on the preferred sale venue. For instance, heterogeneous effects of sale venue are found for condition, size, row spacing, and region. At the same time, there is no evidence of heterogeneous impacts for planter brand and state farming economy class. Weak evidence of heterogeneous effect is found for seasons as well.

4.4 CONCLUSIONS

This paper studied the impact and determinants of selling used planters through different selling venues, including online auctions, in-person auctions, and third-party auctions. Our analysis showed that sales venues can influence selling price of planters.

Moreover, I found that planter-specific attributes had the most significant influence on its sale price. Specifically, size, brand, and age were consistently influential factors across all three sale platforms.

This study showed that location and time were the crucial components of the sellers' venue decision. In general, owners who had newer planters with more advanced options, better conditions, and smaller sizes tended toward in-person auctions as their preferred sale venue. In contrast to factors influencing in-person auction choices, planter owners who owned older planters with poorer conditions and larger sizes tended to sell through third-party auctions. Ultimately, owners of old planters with conventional row structures in states of weaker economies chose online auction platforms to sell their used equipment.

Data availability was a challenge in the this work. Although the initial dataset contained a fair number of observations, the final sample was much smaller due to missing observations. Notwithstanding the relatively limited number of observations, this work offers valuable insights into finding influential factors of sale venue selection and their impacts on prices of used planters, an inseparable component of farming.

Another limitation of this study was the lack of detailed variables relevant to equipment-specific features and states' financial health indices in the agricultural sector over time, and the distance that sellers need to travel to sell their items. Despite its limitations, the study certainly adds to our understanding of how sellers choose a particular type of auction over the others and how the planters' price moves alongside its influential factors.

With the recent pandemic, I expect COVID-19 to introduce a heavier load of web-based auctions due to the nationwide lockdowns. This would be a fruitful area for future work, especially using a difference-in-difference method to assess the hikes in online auctions during COVID-19 and post-COVID-19 compared to pre-COVID-19 auctions.

4.5 TABLES

Table 4-1. Summary Statistics of Each Variable and Their Definitions

Variable	Definition	(A) Aggregate			(B) Venue-Specific Average		
		Mean	S.D.	Range	Online	IP [(a)]	TP [(b)]
Price	Final sale price (1000 USD)	18.66	24.57	.1-190	17.61	27.17	14.82
Auction Channel	Auction Venue Channel [*i*]*	0.62	0.77	0-2	2	1	0
Make	Planter make [*i*]	1.31	0.80	0-3	1.21	1.31	1.35
Condition	Planter condition [*i*]	0.77	0.49	0-2	0.82	0.91	0.69
Size	Number of planter rows [*i*]	1.35	1.31	0-3	1.49	1.11	1.42
Row Type	Row Type [*i*]	0.16	0.12	0-1	0.02	0.02	0.01
Class	States' economic class (state's average farming income) [*i*]	0.61	0.49	0-1	0.80	0.63	0.55
Region	Farm production expenditure regions [*i*]	1.73	0.71	0-3	1.33	1.95	1.74
Trend Auction	Searches for online auction	73.75	8.78	55-95	76.62	72.90	73.23

Notes: [(a)] I.P.: In-Person Auction, [(b)] T.P.: Third-Party Auction, * '*i*' is noted between brackets to indicate categorical variables. Categorical variables can also be recognized by their corresponding values under column 'Range.'

Table 4-2. Endogenous Switching Regression Results of Sale Prices

Outcome: log(price)	(A) Online	(B) In-Person	(C) Third-Party
Make (ref: case I.H.) [a]			
John Deere	.28** (.10)	0.29** (.09)	0.29*** (.07)
Kinze	.36** (.13)	0.32** (.12)	0.28** (.09)
Condition (ref: fair)			
Good	.31 (.35)	-0.32 (.39)	0.60*** (.12)
Excellent	.68 (.43)	-0.24 (.40)	0.76*** (.16)
Size (ref: very small)			
Small	.34*** (.08)	0.34*** (.07)	0.14* (.06)
Medium	.49*** (.10)	0.56*** (.08)	0.33*** (.07)
Large	.89*** (.16)	0.83*** (.15)	0.24* (.11)
Row spacing (ref: Low)			
Medium	.25 (.18)	-0.13 (.12)	0.31** (.11)
Large	-1.33*** (.39)	-0.37* (.17)	-0.19 (.14)
Region (ref: west)			
Plain	-.23 (.14)	-0.63 (.48)	-0.06 (.45)
Midwest	-.27 (.20)	-0.72 (.51)	0.02* (.46)
East	-.66* (.26)	-0.92 (.52)	-0.53 (.47)
Age	-7.89*** (.75)	-7.20*** (.70)	-12.16*** (.53)
Age-squared	.80 (.47)	0.45 (.52)	1.13* (.45)
Constant	9.23*** (.36)	11.35*** (.69)	9.37*** (.48)
Observations	568	568	457
R-squared	.82	.70	.77
Adjusted R-squared	.81	.68	.77
F-statistic	46.81	37.56	80.13

Notes: The Endogenous Switching Regression Results of Sale Prices for Each Auction Channel are reported. Standard errors are in parentheses. The reference variable categories are dropped to avoid perfect collinearity. [a] The categories inside parenthesis denote the reference variable group. Variables' definition and their corresponding units of measurements are provided in Table 1. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

Table 4-3. ESR Results of the Selection Equation

Relative probability sold on channels: (ref: online)	(A) In-Person	(B) Third-Party
Make (ref: case I.H.) [(a)]		
John Deere	.39 (.20)	.27 (.18)
Kinze	.47 (.26)	.48* (.23)
Condition (ref: fair)		
Good	.09 (.77)	-.94* (.40)
Excellent	.94 (.83)	-.68 (.54)
Size (ref: very small)		
Small	.06 (.17)	.32* (.15)
Medium	-.01 (.20)	.25 (.18)
Large	-.28 (.36)	.18 (.31)
Row Spacing (ref: low)		
Medium	.44 (.31)	.26 (.30)
High	.94 (.52)	.53 (.50)
Row structure (ref: conventional)		
Split rows	.32 (.19)	.40* (.18)
Quarter (ref: quarter 1)		
Quarter 2	-.19 (.18)	-81*** (.17)
Quarter 3	.88** (.27)	66** (.25)
Quarter 4	.37 (.19)	36* (.17)
Region (ref: west)		
Plain	0.92 (.54)	1.82*** (.54)
Midwest	1.56** (.54)	1.89*** (.54)
East	1.70** (.61)	1.56* (.65)
Age	-8.39*** (1.75)	-1.03 (1.66)
Age-squared	.77 (2.00)	1.65 (1.54)
Constant	-1.74 (.92)	-.96 (.68)
Observations	568	457
LL	-403.08	-344.05

Notes: Endogenous switching regression results of selection equation relative to the reference venue type are reported. Standard errors are in parentheses. The reference variable categories are dropped to avoid perfect collinearity. [(a)] The categories inside parenthesis denote the reference variable group. Variables' definition and their corresponding units of measurements are provided in Table 1. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

Table 4-4. The Results of TSLS Model First-Stage

Auction Venue Channel	(A) Online	(B) Third-Party
Make (ref: Case I.H.)		
John Deere	.74 (.14)	1.28 (.28)
Kinze	.54*** (.12)	1.09 (.23)
Condition (ref: fair)		
Good	1.05 (.22)	.48*** (.08)
Excellent	.14*** (.08)	.13*** (.04)
Size (ref: very small)		
Small	1.04 (.22)	1.18 (.21)
Medium	1.07 (.33)	1.03 (.19)
Large	2.76*** (.78)	1.78*** (.19)
Region (ref: East)		
Plain	15.89*** (12.89)	6.74*** (4.39)
Midwest	3.41* (2.22)	2.21 (1.27)
West	18.57*** (19.19)	2.63 (1.97)
Quarter (ref: Q1)		
Q2	1.09 (.24)	.49** (.15)
Q3	.41*** (.10)	.50* (.21)
Q4	.64 (.23)	.49*** (.11)
State Economy Class (ref: low)		
High Income	1.55 (.81)	.52 (.27)
Trend of Online Auction Search	1.03*** (.01)	1.00 (.01)
Constant	.01*** (.01)	1.41 (1.51)
Pseudo R-squared		0.13
Probability ()		0.00
Observations		2,734

Notes: The reference variable categories are dropped to avoid perfect collinearity. The categories inside parenthesis denote the reference variable group. The year 2017 is considered as the reference year for Online auctions. Variables' definition and their corresponding units of measurements are provided in Table 1. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% levels.

Table 4-5. The Results of TSLS Model Second-Stage

Log (price)	(1)	(2)	(3)
	Online	In-Person	Third-Party
Prob(venue)	1.63*** (.43)	1.90*** (.52)	2.13*** (.36)
Make (ref: Case I.H.)			
John Deere	-.21 (.15)	-.09 (.13)	-.14 (.11)
Kinze	.26 (.18)	.58*** (.14)	.37*** (.12)
Condition (ref: fair)			
Good	1.77*** (.12)	1.86*** (.14)	1.62*** (.08)
Excellent	3.15*** (.36)	3.25*** (.25)	3.42*** (.22)
Size (ref: very small)			
Small	.77*** (.12)	.75*** (.09)	.66*** (.07)
Medium	1.31*** (.16)	1.21*** (.11)	1.36*** (.10)
Large	.03 (.11)	-.53*** (.11)	-.10 (.07)
Constant	6.13*** (.44)	5.91*** (.44)	5.88*** (.31)
Control Variables	YES	YES	YES
R-squared	0.54	0.61	0.56
Observations	489	743	1,502

Notes: The reference variable categories are dropped to avoid perfect collinearity. The categories inside parenthesis denote the reference variable group. Variables' definition and their corresponding units of measurements are provided in Table 1. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% levels. Robust standard errors are reported in parentheses.

Table 4-6. Results of Heterogeneous Effects of Used Planter Sale Venues

Log of Price	(A) No interactions	(B) IP interactions	(C) Online interactions
Auction Venue (ref: Third Party) [a]			
In-person	1.78*** (.42)		
Online	.65** (.29)		
Make (ref: Case IH)			
John Deere	.33*** (.08)	.02 (.11)	-.02 (.12)
Kinze	.30*** (.09)	.01 (.14)	.03 (.14)
Condition (ref: fair)			
Good	.42*** (.11)	-.88** (.34)	.02 (.15)
Excellent	.67*** (.14)	-1.02*** (.36)	.48* (.27)
Size (ref: very small)			
Small	.20*** (.06)	.06 (.09)	.22** (.09)
Medium	.41*** (.07)	.20* (.11)	.11 (.11)
Large	.23*** (.12)	.50* (.25)	.58*** (.17)
Row spacing (ref: low)			
Medium	.43*** (.10)	-.38** (.17)	-.05 (.14)
High	-.08 (.19)	-.12 (.25)	-.77*** (.20)
Row structure (ref: conventional)			
Split rows	.31*** (.06)	.03 (.09)	.01 (.09)
Region (ref: west)			
Plain	.50*** (.06)	-.72*** (.20)	-.54* (.29)
Midwest	.60*** (.06)	-.80*** (.20)	-.51* (.29)
East	.10 (.16)	-.56** (.22)	-.25 (.38)
Quarter (ref: quarter 1)			
Quarter 2	-.16* (.09)	.01 (.14)	-.15 (.12)
Quarter 3	.05 (.08)	-.11 (.11)	-.19* (.11)
Quarter 4	.04 (.05)	-.06 (.08)	-.15 (.10)
Age	-.12*** (.01)	-	-
Age-squared	.00*** (.00)	-	-
Intercept	9.80*** (.24)	-	-
Mean dependent variable			10.24
SD dependent variable			(.89)
Number of observations			847.00
R-squared			.80
Akaike crit. (AIC)			977.08
Bayesian crit. (BIC)			1261.58

Notes: [a] T.P. denotes Third-Party. The categories inside parenthesis denote the reference variable group. The reference variable categories are dropped to avoid perfect collinearity. Variables' definition and their corresponding units of measurements are provided in Table 1. Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% level.

CHAPTER 5. CONCLUSIONS

Public health remains an important issue in the US and the World. The topic of public and personal health and its intersection with food, and consequently, the agricultural industry has a storied history in the literature. The consumption of healthy food products, food-health programs, and policies related to food- and health-payments are important subtopics within this space.

Based on the three distinct but interrelated projects that explored the intersection of agriculture, nutrition, and economics, this dissertation provides several significant contributions to our understanding of how policies and programs impact public health and economic outcomes. In this study, I developed techniques to investigate the intricate correlation between food policies and health across two projects. I then extended this investigation to a third project, wherein I explored how decisions and choices could result in systematic fluctuations in post-decision outcomes.

Our overall findings suggest that policies and programs aimed at improving diets should be targeted more effectively, as their effects may be less immediate and more significant in the long run. Additionally, our analyses show that individuals of different racial and ethnic backgrounds may experience varying outcomes. Some minority groups exhibit better management of their health outcomes and status when receiving food assistance programs compared to others, indicating that policy makers and program managers need to reassess their public health targets.

Finally, several factors including geographic-specific features and time-varying elements can influence consumers' decision-making process when selecting a preferred market to achieve their desired level of profit or utility. In light of the global outbreak, which has affected individuals' lifestyles in their health status as well as the market dynamics, I recommend that policymakers reassess the infrastructure to better facilitate consumers' needs and desires.

Taken together, the findings of this dissertation underscore the importance of considering the intersection of agriculture, nutrition, and economics when developing policies and programs that impact public health and economic outcomes. Moreover, the study highlights the need for researchers to use appropriate statistical methods to account for potential biases that may affect estimates of program impacts. Overall, this dissertation contributes to our understanding of how policies and programs can be optimized to promote public health and economic well-being.

APPENDICES

CHAPTER 2 APPENDICES

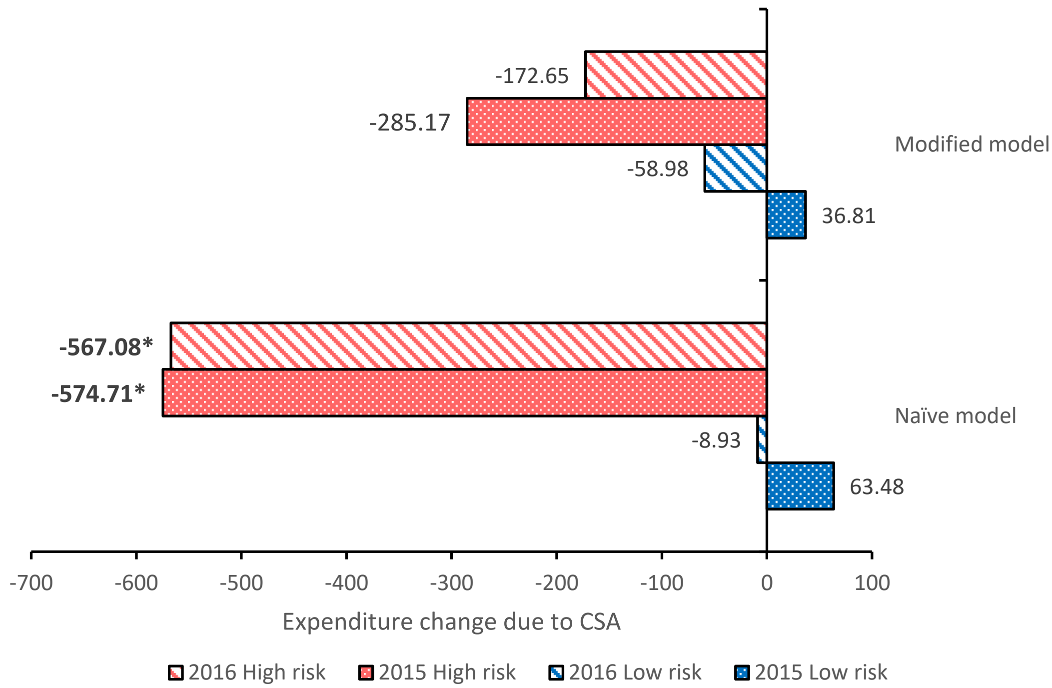

Figure 5-1. The effect of CSA participation by cohort
Note: The effect of CSA participation on diet-related medical expenditures by model, baseline expenditure categories, and year of enrollment in CSA.

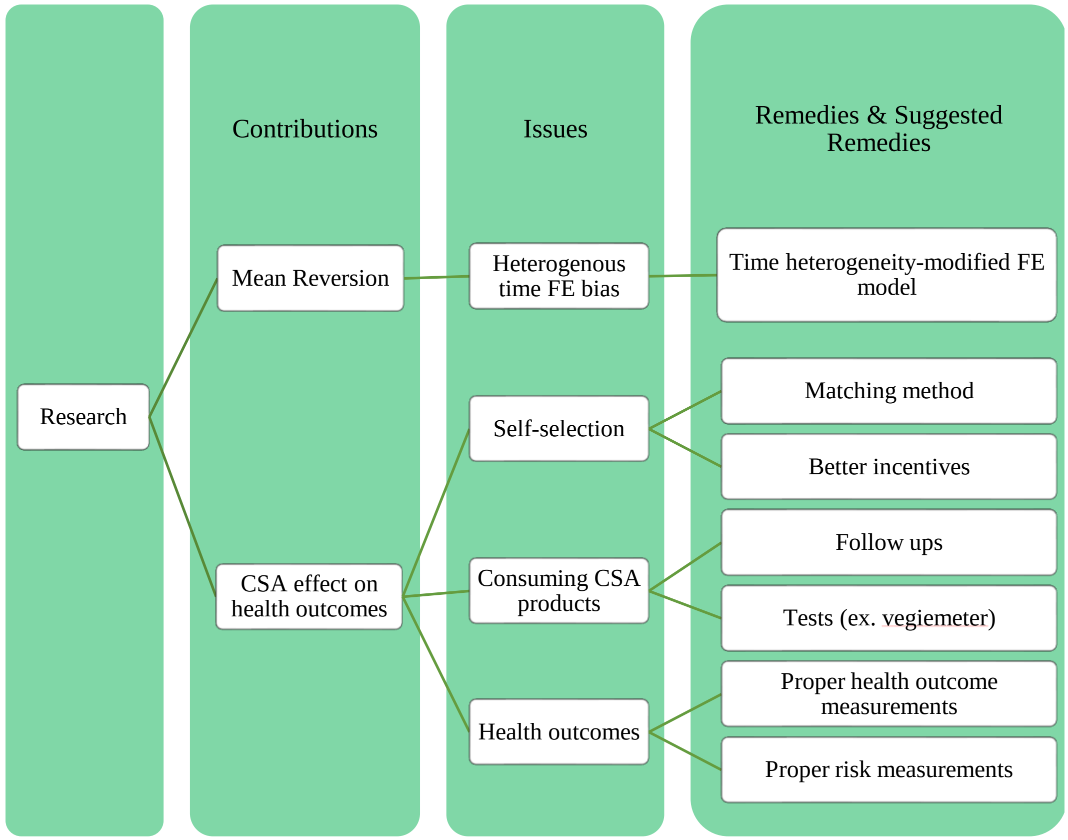

Figure 5-2. Contributions flowchart

Schematic flowchart of this project's contribution, issues, remedies, and suggested remedies to those issues.

Table 5-1. Evidence of Mean Reversion

Dependent Variable: Diet-related medical expenditures ($)	(1) FE	(2) HTFE
2015 CSA participants		
lo_expend	5.93	36.81
	(55.35)	(111.45)
hi_expend	-430.87***	-285.17
	(172.46)	(245.71)
2016 CSA participants		
lo_expend	5.93	36.81
	(55.35)	(111.45)
hi_expend	-430.87***	-285.17
	(172.46)	(245.71)
Controls	YES	YES
Individual FE	YES	YES
Time FE	YES	NO
Time by Baseline Expenditure FE	NO	YES
Observations	27,948	27,948

Note: Standard deviations are in parentheses. Triple asterisks (***) indicate statistical significance at the 1% level. Control variables include gender, age, and number of medical claims.

Table 5-2. Matching Results

A) Balance Match Results
Aggregate Baseline Diet-Related Medical Expenditure

	Difference Values Between Control and Treated Participants			
	Group 2015		**Group 2016**	
Balancing variables	Before Match	After Match	Before Match	After Match
Gender (Male=1)	-0.29***	0.08	0.06	-0.05
Date of birth (Year)	8.10***	0.80	6.80***	0.40
Number of Claims				
Baseline period 1	-1.82***	-0.25	-1.80***	-0.32**
Baseline period 2	-0.93	0.00	-2.25***	-0.27
Baseline period 3	-1.84***	0.17	-1.51***	-0.27*

B) Estimated ATTs

Outcome variable ($)	**Group 2015 [n=12]**	**Group 2016 [n=22]**
Post-intervention period 1 expenditure	-336.37	444.90*
	(344.74)	(230.39)
Post-intervention period 2 expenditure	-115.04	797.72
	(279.62)	(803.34)
Average post-intervention expenditure	-225.7	621.31
	(234.55)	(407.34)

Note: Single, double, and triple asterisks (*, **, ***) indicate [statistical] significance at the 10%, 5%, and 1% levels. Standard errors are in the parentheses. Number of treated individuals (who received CSA and were classified as high-baseline medical expenditure individuals) are reported in square brackets.

CHAPTER 3 APPENDIX

Table 5-3. Endogeneity bias and self-selection bias check

	(1)	(2) (Augmented Regression)
Dependent Variable	$SNAP$	$A1C$
$A1C$	-0.06	
	(0.08)	
$SNAP$		-0.44
		(1.60)
$\hat{\varepsilon}_{SNAP}$		0.05
		(0.33)
Constant	2.28	10.54
	(1.48)	(1.42)
Controls	YES	YES
Observations	408	408
F-statistic	1.87	3.07

CHAPTER 4 APPENDICES

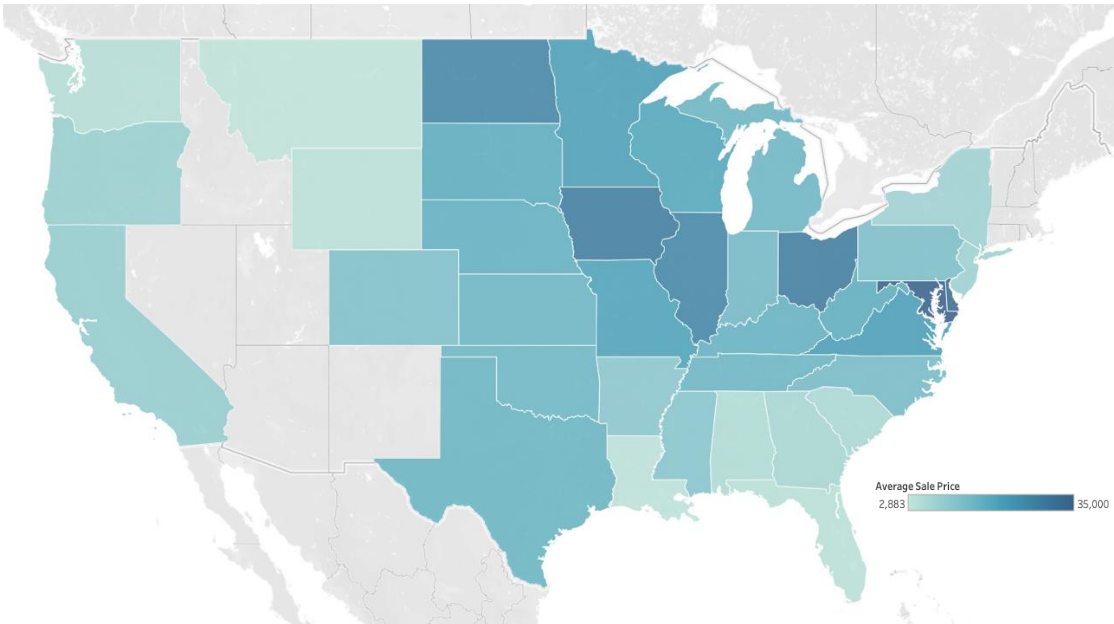

Figure 5-3. Average Price ($) of Planters Across States

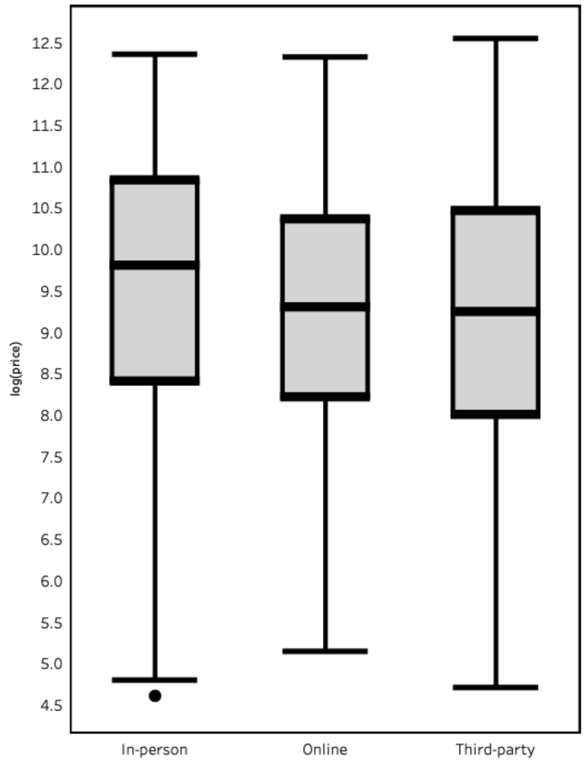

Figure 5-4. Box plot of planters sale value over each auction venue

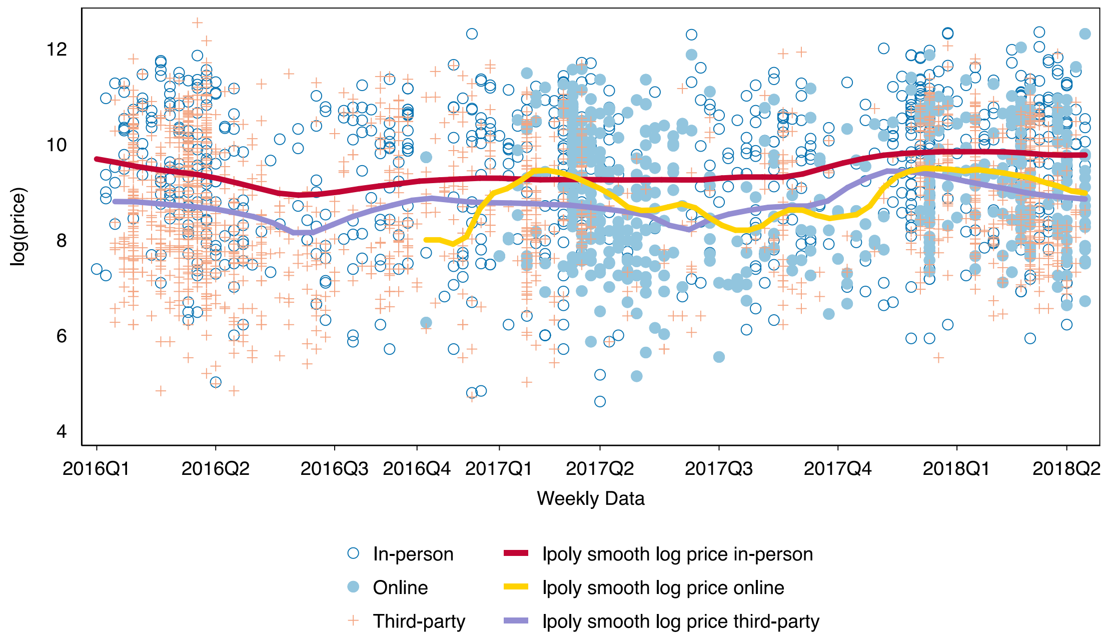

Figure 5-5. Planter sale value by auction type

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Shuoli Zhao, Saber Feizy, and Wenying Li. “Consumers ’Reference Dependency in Labeling: Evidence from Plant-Based Meat Alternatives” Southern Agricultural Economics Association (SAEA) Annual Meeting. Oklahoma City, Oklahoma, February 4-7, 2023.

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Saber Feizy, Steven Buck, Jairus Rossi, Timothy Woods, and Shuoli Zhao, “Mean Reversion Is Misleading: The Effect of A CSA Voucher Program on Short-Run Diet-Related Medical Expenditures” Southern Agricultural Economics Association (SAEA) Annual Meeting. Oklahoma City, Oklahoma, February 4-7, 2023. Dissertation Job Market Paper Competition Presentation – *3rd Place Award Winner.*

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Saber Feizy and Micheal Reedl "The Effect of Recent Iranian Exchange Rate Volatility on Domestic Prices," Agricultural & Applied Economics Association (AAEA) Annual Meeting. Kansas City, Missouri – Virtual Conference, July 26-28, 2020. Selected paper abstract.

Saber Feizy and Mahmood Daneshvar, “Evaluating the Recreational Value of Telar-Park in Iran; the Individual Travel Cost Method,” International Conference on Sustainable Development, Strategies and Challenges. Tabriz, Iran, 2014.

Saber Feizy, Nima Ajam, and Mahmood Saboohi, “Using single-objective fuzzy linear programming to determine cropping patterns,” National Conference of Agricultural Development. Tehran, Iran, 2014.