DISSERTATION

THREE ESSAYS ON PRODUCER RESPONSE TO INFORMATION DISCLOSURE

Submitted by

Shuiqin Yu

Department of Agricultural and Resource Economics

In partial fulfillment of the requirements

For the Degree of Doctor of Philosophy

Colorado State University

Fort Collins, Colorado

Fall 2023

Doctoral Committee:

Advisor: Marco Costanigro

Jesse Burkhardt
Dana Hoag
Harvey Cutler

ABSTRACT

THREE ESSAYS ON PRODUCER RESPONSE TO INFORMATION DISCLOSURE

This dissertation consists of three chapters studying how information and beliefs affect producers' behavior and decision making.

The first chapter studies the effect of the Local Inspector Value Entry Specification (LIVES) program on restaurant hygiene in North Carolina. The LIVES Program, a collaboration between Yelp.com and municipalities, enables the display of restaurant inspection reports on Yelp's platform, simplifying access for consumers. Combining individual restaurant inspection data and restaurant level demographic data from Yelp.com, this study employs a difference-in-difference approach and geographic regression discontinuity design to analyze the LIVES program's impact on restaurant hygiene. The difference-in-difference analysis reveals a 1.143-point improvement in inspection scores for treated restaurants. The geographic regression discontinuity method, utilizing a neighboring county as a control group, corroborates the LIVES program's positive influence.

The second chapter examines the effect of online consumer reviews on restaurant workers' wages. Online consumer reviews significantly influence the demand for experience goods, including movies, books, and restaurant meals. However, research on the impact of online reviews on restaurant workers' wages remains scarce. Utilizing decade-long panel data of quarterly consumer reviews and restaurant wages, this study demonstrates that an increase in average star ratings causes restaurant workers' wage growth. Notably, the effect varies across chain, major chain, and independent restaurants.

The final chapter studies how Colorado farmers' and ranchers' subjective beliefs about the cost of adoption affect their intention to implement conservation practices. Promoting the adoption of conservation practices among farmers is challenging. Despite extensive research into farmers' reluctance to participate in conservation programs, few studies investigated how farmers' personal beliefs on the cost of adopting conservation practices affect their willingness to participate in those programs. This study adds to the literature by surveying over 150 Colorado farmers on their preferences for monetary and technical support regarding conservation tillage, soil testing, filter and buffer strips, and controlled-release fertilizers. Results from a choice experiment indicate that respondents' beliefs about costs can explain a large portion of the variation in farmers' willingness to adopt conservation practices.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my advisor, Professor Costanigro, for having confidence and patience in me during these years. I would also like to thank everyone on the committee, Professor Burkhardt, Professor Hoag, and Professor Cutler, for their feedback and help on the dissertation. I am grateful to work under the supervision of this committee.

Secondly, I would like to express gratitude to my dear husband, Vladyslav Anderson, who has been by my side during the ups and downs and continually motivated me to be better. From formatting assistance to resolving computer issues, Vlad has been an indispensable source of technical support.

Thirdly, I extend my heartfelt thanks to my parents for their constant love and support. They brought me into this world and raised me. While they never had the opportunity to attend college, they gave me the very best they could. I am forever indebted to them.

Lastly, I want to thank the friends I have made along this journey. Life would be dull without them. Our soccer matches, Christmas caroling, BBQ gatherings, and birthday celebrations will forever remain cherished memories in my heart.

TABLE OF CONTENTS

1 THE EFFECT OF PUBLIC INSPECTION INFORMATION DISCLOSURE FOR CONSUMERS ON RESTAURANTS' HYGIENE QUALITY

1.1 Introduction

Technological innovation has changed the way consumers search for food away from home. This empirical study seeks to determine if greater consumer access to information on restaurant hygiene performance provides an incentive to improve restaurant hygiene quality. Consumers today are increasingly using online search websites to locate restaurants and reading consumers' reviews to decide which restaurants to patronize. Yelp.com is one of the most popular websites designed to facilitate this search and decision process. After Yelp expanded from a desktop website to a mobile application, it is now used by 45.18% of consumers as their primary aid for deciding upon a business location (ReviewTrackers, 2020).

Acknowledging the crucial role of hygiene in restaurant selection, Yelp created the Local Inspector Value-Entry Specifications (LIVES) program with San Francisco and New York City in 2012 (Yelp, 2018). The LIVES program enables municipalities to disclose restaurant inspection information on Yelp. As of September 2023, 215 municipalities were partnering with Yelp to publish restaurant inspection information on its platform. Disclosing the restaurant inspection information on Yelp reduces the information asymmetry about restaurant hygiene quality between consumers and restaurants, increasing the saliency of hygiene quality in the market, creating a natural platform to investigate whether restaurants respond to this form of online disclosure regulation.

In recent years a growing body of food safety policies emerged in the wake of increasing public concerns over outbreaks of foodborne illness in the United States that resulted from compromised ingredients, unsanitary environments, and improper food handling. Across the nation, various municipalities have progressively instituted policies aimed at mitigating foodborne illness outbreaks by enhancing the dissemination of product quality information to consumers. One such policy is the Food Safety Modernization Act (FSMA), legislated in 2011, which provides a systematic approach to monitoring food safety regulations (Hoffman, 2011). In another example of such policies, Los Angeles County has mandated restaurants to display hygiene quality grade cards on their windows since 1998 (Jin and Leslie, 2003).

This study utilizes a panel dataset on restaurant hygiene score to examine whether public disclosure of restaurant inspection information through the LIVES program improves restaurants hygiene performance. Using a difference-in-differences approach and a geographic regression discontinuity design, this study finds evidence of positive and significant restaurant hygiene quality improvements resulting from increased consumer access to this information.

The development history and background of the LIVES program are detailed in the background section. The literature review section presents a comprehensive analysis of prior theoretical and empirical studies on the effect of information on product quality. The data section delves into the empirical data and its specifications used in the analysis. The results and implications are discussed in the empirical specification section. In the robustness check section, I test the sensitivity of empirical results against different specifications. Lastly, the conclusion section summarizes my main findings.

1.2 Background

The federal regulatory framework for the oversight of restaurants in the U.S. involves both the Food and Drug Administration (FDA) and various state/territorial regulatory agencies. The FDA developed the Food Code, a model aimed at protecting public health and guaranteeing safe and uncontaminated food for consumers (FDA, 2017). Though adopting the Food Code is recommended, it is not obligatory. Nearly all states have adopted it as of December 31, 2020, with California being the sole exception (FDA, 2020). Despite the disparities in state or territorial regulations, restaurants in the U.S. are generally subject to inspections at least once a year. The most common types of inspections conducted at restaurants or retail food services include routine inspections, follow-up inspections, and inspections initiated due to complaints. Other types of inspections exist, varying within each state or territory. The regulations or codes governing restaurant inspections vary from state to state and, in some cases, from city to city. For example, all cities in North Carolina share the same inspection criteria for food and facility inspections, while the inspection criteria vary across the counties of Colorado.

There are three main restaurant grading systems: the points-deduction system, the letter grade system, and the violation accumulation system. The typical points-deduction system scores start with 100 points, with points deducted based on varying critical levels and categories of the violations. Counties in North Carolina have adopted this grading system. The letter grade system utilizes grades A, B, and C to indicate the level of compliance with hygiene standards and food handling practices, and the assignment of the range of points to grades A, B, and C varies from city to city. For example, in Los Angeles, grade A is assigned to a restaurant whose inspection score ranges from 90 to 100 points, which denotes “Generally superior in food handling practice” (Los Angeles County, 2023). Grade B is assigned to a restaurant with an inspection score ranging from 80 to 89 points, representing “Generally good in food handling practices”. Grade C is assigned to restaurants with an inspection score of 70 to 79, representing the “Generally acceptable” hygiene condition. The violation accumulation system assigns each violation a score and then sums them together. Boulder county in Colorado uses this violation accumulation system.

In cities like New York and Los Angeles, the inspector will issue a grade card or a scorecard to the restaurant manager at the end of the inspection. These cards are required to be visibly displayed so that consumers know the result of the most recent inspection. The specific requirements for the card's placement vary from city to city. Some cities require the card to be displayed on a window while others require the card to be posted near the public entrance. These display requirements aim to increase consumers' awareness about the level of hygiene found in restaurants. In addition, hygiene reports for restaurants in some cities can often be found in local newspapers or broadcasted by local radio stations. It is also common to find restaurant inspection reports on the state or local municipality websites.

In 2012, Yelp initiated a collaboration with the cities of San Francisco and New York to launch the LIVES program (Yelp, 2018).[1] This program allows government inspection agencies to share inspection data with Yelp's mobile and desktop users, who can view whether a restaurant passed its previous inspection and whether there were critical or non-critical violations (in other cases, labeled as high-risk or low-risk).

By September 2023, 215 municipalities in the U.S. had partnered with Yelp to bring inspection information to consumers. These municipalities include cities and counties from Alaska, California, Colorado, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Tennessee, and Texas. Although this program is successful in many municipalities, technological issues have created potential barriers for some cities to post their inspection results

[1]The website can be retrieved at https://www.yelp.com/healthscores/feeds .

on Yelp. According to research from the open data company Socrata (Shueh, 2015), many U.S. cities neither publish restaurant inspection information nor use a digital-friendly format to present it. Based on the discussions with a local county officer, the existing contentment within the community with the current state of affairs might also deter municipalities from considering participation in this program.

1.3 Literature review

As Stigler (1961) points out, searching for product quality information is often more complicated than searching for price information. While price information for meals in a restaurant can be easily found on the restaurant's website or from the physical menu, details about a restaurant's food and service quality are more challenging for consumers to discover, putting consumers at a disadvantage. Akerlof (1970) first describes the market inefficiencies arising with experience goods when sellers are more knowledgeable than buyers about the quality of their products. Such information asymmetry between restaurants and consumers can place consumers at a disadvantage in the restaurant industry.

There are numerous ways to mitigate asymmetric information between sellers and buyers, including issuing guarantees, developing brand-name goods, creating retail chains, and employing licensing practices (Akerlof, 1970). These methods attempt to create a standard for signaling the quality of products and services. Product or service quality reports from an independent party function similarly by increasing available product or service quality information to consumers, potentially mitigating the asymmetric information and altering consumer and producer behaviors.

A growing body of literature has investigated consumer reactions to information regarding the quality of products or services, with a significant portion of this research focusing on the field of health economics (Beaulieu, 2002; Wedig and Tai-Seale, 2002; Jin and Sorensen, 2006; Dafny and Dranove, 2008; Bundorf et al., 2009). Beaulieu (2002) and Dafny and Dranove (2008) confirm consumers' responsiveness to service quality information across health plan choices. Wedig and Tai-Seale (2002) and Jin and Sorensen (2006) verify consumer responsiveness to service quality information concerning health insurance choices. Bundorf et al. (2009) also confirm consumer responsiveness regarding health clinic selections. These studies investigate the introduction of report cards, which are published ratings on consumers' choices, and find evidence of consumer behavioral change in response to healthcare service quality information. In addition, Pope (2006) finds evidence of patients' and students' responses to hospital and college rankings. Similarly, Hastings and Weinstein (2008) confirm the positive effect of school test score information on public school choices of low-income families.

Another stream of research has examined how consumers' perceptions and behavior are affected by restaurant hygiene. The empirical works conducted by Henson et al. (2006) and Aksoydan (2007) suggest that consumers choose restaurants based on their subjective judgment of restaurant hygiene. Utilizing feedback from focus groups and a postal survey conducted in Ontario, Canada, Henson et al. (2006) conclude that both inspection results and the number of customers in a restaurant contribute to consumers' dining choices. Similarly, Aksoydan (2007) examines survey results from 243 academic staff in Ankara, Turkey, to find that restaurant hygiene information greatly influenced consumers' restaurant decisions. Consumers' responses to letter grade hygiene information and numerical hygiene scores were studied by Kang (2015), who finds that A grades and higher overall inspection scores were associated with higher perceived restaurant quality. Further, Luca (2016) shows that a Yelp rating improvement of one star leads to a 5-9% increase in restaurant revenue.

Many producers value product or service quality information because consumers' awareness of a positive signal of product or service quality often increases demand. Consumers' awareness motivates producers to adjust their practices to achieve higher quality ratings. Indeed, a growing collection of empirical research shows how producers react to information disclosure about their product or service quality. These studies find that information disclosure has many impacts, including reducing violations of drinking water standards from community drinking water suppliers in Massachusetts (Bennear and Olmstead, 2008), as well as reducing pollution from pulp and paper plants in India (Powers et al., 2008). Information disclosure has also improved restaurant hygiene quality in Los Angeles County (Jin and Leslie, 2003, 2009) and the service quality of nursing homes (Lu, 2012).

However, some existing empirical research implies that increased access to quality signals can have indirect, negative consumer impacts. Dranove et al. (2013) find that the introduction of report cards on individual healthcare providers has enticed some doctors to reject providing treatment to severely ill patients to achieve better quality scores on healthcare report cards. This selection behavior has resulted in worse community health outcomes and sicker patients.

Although consumers' responses to report cards or grades on restaurant hygiene have been studied by economists, there is quite a gap in understanding the disclosure of restaurant hygiene information on restaurants' hygiene quality. Jin and Leslie (2003) study the effect of restaurant hygiene grade cards on restaurant hygiene quality in Los Angeles from 1996 to 1998. They find that the introduction of grade cards positively affects restaurant hygiene, yielding insights into how mandatory and voluntary disclosure affect restaurant hygiene quality. However, their study does not capture the impact of new ways of disclosing hygiene quality information online.

Makofske (2020) estimates that disclosing restaurant hygiene information on Yelp led to a restaurant inspection violation score reduction of 12-14% in Louisville, KY. Makofske's (2020) paper is very similar to this study, as both studies examine the effect of posting health inspection information on restaurant hygiene quality. While Makofske (2020) only analyzed inspection violation data from one city with the information disclosure program, this study employs data from multiple cities. Additionally, this study's design offers a more natural experimental setting by contrasting treated and control groups from various cities, enabling me to accurately examine the LIVES program's causal effect on restaurant hygiene quality. Finally, this study provides new evidence in understanding the role that information plays in a monopolistic competition market like the restaurant industry.

1.4 Empirical framework

The goal of this study is to measure the causal effect of the LIVES program on restaurant hygiene quality. The LIVES program began in 2012 with the purpose of increasing consumers' access to the latest restaurants' hygiene information and helping consumers make their dining choices (Yelp, 2018). Prior to the LIVES program, consumers had to search for restaurant inspection reports on municipality websites, local newspapers, and other media outlets, which sometimes could be outdated or difficult to interpret.

North Carolina serves as an excellent case study for analyzing the impacts of the LIVES program due to a multitude of unique factors. To begin with, all the counties in this state have utilized the same inspection form since 2013, ensuring uniformity and comparability of inspection scores across the board, a feature not found in other states participating in the LIVES program. Additionally, North Carolina consists of 98 counties, of which five have participated in the LIVES program, allowing their restaurant inspection data to be visible to consumers on Yelp. This situation allows me to pick treated and control groups to mimic a natural experiment, identifying cause effect by comparing a treated group that participated in the LIVES program with a similar control group that did not participate, I can potentially find empirical evidence supporting the claim that the LIVES program has caused changes in the outcomes of the treated group.

Figure 1.1 is the North Carolina State map, highlighting the five counties that participated in the LIVES program. Specifically, Orange, Wake, Harnett, and Cumberland counties are in the middle of North Carolina, while Mecklenburg County sits on the west side of the state.

Figure 1.1: Counties Participating in the LIVES Program in North Carolina.[2]

The LIVES program is gradually being implemented across North Carolina. According to Yelp (2018), the steps for a municipality to participate in the LIVES program include: 1) create a feed under Yelp's data requirements, 2) host the feed on either an HTTP or HTTPS address, and

---

[2] Source for Figure 1.1: https://mapchart.net/usa-counties.html

3) send an email to Yelp attaching a link to the feed. Upon receipt of the email, Yelp will validate, test, and launch the data.

Wake County was the first county in North Carolina to participate in the LIVES program in October 2013, followed by Orange County, which joined in September 2014. More than two years later, Cumberland County published inspection data on Yelp in April 2017, and Mecklenburg did the same in May 2017. Harnett County was the newest member in this group, starting in the first quarter of 2018. According to Susan Cole, a program manager from the health department in Mecklenburg County, their partnership with Yelp aligns with their objective and emphasis to safeguard the public's health and safety (Douglas, 2017).

I use two empirical approaches to study the causal effect of the LIVES program on restaurant hygiene quality: the Difference in Differences (DID) approach and the Geographic Regression Discontinuity (GRD) approach. Both approaches require a treated group and a control group. Comparing the difference between a treated group and a control group, with their difference being the absence of treatment, helps establish a causal inference from the treatment (Dunning, 2012). Applying two empirical methods helps me critically evaluate the estimated effect of the LIVES program on restaurant hygiene.

I chose Orange County as the treated group and Durham County as the control group to study the effect of the LIVES program on restaurant hygiene quality. This selection is based on several reasons. First, Mecklenburg and Wake Counties are the two most populous counties. This causes difficulty in finding a control group with a similar population density so that the treated and control groups are comparable. Second, Harnett County has only participated in the LIVES program since the first quarter of 2018, resulting in fewer inspection data observations. Third, the

GRD approach requires that the treated and control counties are adjacent — a condition that Orange County and Durham County satisfy.

1.5 Data for Difference in Differences Approach

The dataset for the difference in differences study includes restaurant inspection data and restaurant characteristic data, which consists of inspection reports from the treated group (Orange County) and the control group (Durham County). The primary sources for restaurant inspection data for Orange and Durham Counties are the LIVES program and the Durham County websites, respectively. The restaurant inspection data is an unbalanced panel because restaurants have different inspection frequencies.

Each inspection report contains a unique business identification number, inspection date, inspection score, inspection type, and a description of violations. The inspection dates range from January 2013 to February 2019. The inspection scores range from 0 to 100, where a score of 0 signifies total violation of the regulations, and a score of 100 denotes full compliance with all inspection standards. Inspection types fall into three categories: routine, follow-up, and complaint. However, this study only considers routine inspections as they represent the general hygiene quality of each restaurant. Violations are divided into critical and non-critical violations. Critical violations indicate incidents related to foodborne disease outbreaks, while non-critical violations concern minor food handling misconduct.

Restaurant characteristics data for Orange and Durham Counties come from Yelp.com. On Yelp, restaurants are divided into four classifications on the basis of price: inexpensive ($), moderate ($$), pricey ($$$), and ultra high-end ($$$$). However, the dataset in this study only has restaurants in the first three categories. A "$" restaurant denotes that the average price for a meal per person in this restaurant is below $10, "$$" indicates that the price is between $11 and $30, and “$$$” means the price ranges from $30 to $60. Additionally, each restaurant is categorized based on certain attributes such as food ethnicity, speed of food service, cooking method, and table service. For instance, a restaurant could be categorized as “Chinese, fast food”.

Using observational data for causal inference often involves dealing with confounding variables that influence pretreatment control variables. Following Iacus et al. (2011), I use Coarsened Exact Matching to balance the distributions of the covariates in the treated and control groups. The procedure consists of three steps. First, the covariate restaurant category was chosen and then coarsened according to the restaurant classification. For example, Sushi Bar and Japanese are coarsened into the same category. Each restaurant inspection in the treated group within a certain restaurant category falls into a stratum based on the coarsened classification, and it is matched to a corresponding restaurant inspection from the control group. Next, the unmatched observations are excluded so that the number of inspections in the treated and control groups is the same.

Table 1.1 shows the final matching result. This CEM procedure resulted in 2,934 observations in the treated group, and as many observations in the control group. Table 1.1 also reports the summary statistics of the restaurant inspection data from Orange County and Durham County. Orange County has a larger mean inspection score and a less divergent distribution of scores.

Table 1.1: Summary Statistics of Inspection Data from Orange and Durham Counties

County Name	Restaurants	Inspections	Mean Score	Std. Dev of Score
Orange County	162	2,934	97.6677	2.0068
Durham County	395	2,934	96.6154	2.4971

Sample means for the treated and control groups before and after the policy provide a preliminary measure of the effect of the LIVES program. Table 1.2 reports the mean inspection scores for the treated and control groups before and after the introduction of the LIVES program. The "Before" period ranges from January 2013 to September 15, 2014, and the "After" period is from September 16, 2014 to February 2019. Prior to the program's implementation, the mean inspection score for the treated group was 0.25 points higher than that of the control group. However, after the program went into effect, the mean inspection score for the treated group rose to 97.88 points, surpassing the control group's average by approximately 1.34 points. This change is consistent with the hypothesis that the LIVES program may improve inspection scores in the treated group.

Table 1.2: Difference in Differences for mean inspection score

Time period	Group (County)	Obs	Mean	Std. Dev
Before	Treated (Orange)	828	97.1322	2.2484
	Control (Durham)	679	96.8814	2.4272
	Difference		0.2508	
After	Treated (Orange)	2,106	97.8782	1.8623
	Control (Durham)	2,255	96.5353	2.5127
	Difference		1.3429	
	Difference-in-Differences		1.0921	

1.6 Empirical Specification – Difference in Differences Approach

To estimate the effect of joining Yelp's LIVES program on restaurants' hygiene, I adopt a difference in difference (DID) approach. The DID approach allows researchers to use observational data to simulate a natural experiment to uncover a potentially causal relationship by comparing the difference between the treated and control groups before and after the treatment (Angrist and Pischke, 2009).

One core assumption for utilizing the DID approach is the parallel trends assumption (Angrist and Pischke, 2009). This assumption requires that macroeconomic trends, seasonality, and unobserved heterogeneity remain consistent after the treatment. The application of the CEM method creates a quasi-control group that guarantees heterogeneity between the control and treated groups is significantly reduced. The careful selection of the treated and control groups and the application of the CEM is the mechanism ensuring identification of the causal effect of the LIVES program. I use the following regression specification for the estimation:

$$y_{ijt} = \beta_0 + \beta_1 After_t + \beta_2 After_t \times Treat_j + Restaurant_j + Year_t + Month_t + \varepsilon_{ijt} \tag{1.1}$$

where subscript i reflects each individual inspection, j is the restaurant, and t is the time period.

In the regression, y_{ijt} denotes the i^{th} restaurant inspection score for restaurant j at time t. Variable $Treat_j$ is a dummy variable and is 1 if restaurant j resides in a county that participated in the LIVES program and 0 otherwise. $After_t$ is a dummy variable that differentiates the time period before and after the treatment of joining the LIVES program.

The $Restaurant$ fixed effects control for those unobserved, time-invariant factors that can affect hygiene quality in each restaurant, such as food type, operation hours, seating capacities, and so on. The variable $Year$ represents year fixed effect, while $Month$, which represents a set of 11 dummies controlling for seasonality.

Assuming $t = 0$ is the pre-treatment period, and $t = 1$ is post-treatment, the difference of the expected inspection score for the treated group after and before the treatment is:

$$E(y_{ijt}|Treat_j = 1, t = 1) - E(y_{ijt}|Treat_j = 1, t = 0) = \beta_1 + \beta_2 \tag{1.2}$$

and the difference of the expected inspection score for the control group after and before the treatment is:

$$E(y_{ijt}|Treat_j = 0, t = 1) - E(y_{ijt}|Treat_j = 0, t = 0) = \beta_1 \tag{1.3}$$

Thus, the difference of the above differences is:

$$\{E(y_{ijt}|Treat_j = 1, t = 1) - E(y_{ijt}|Treat_j = 1, t = 0)\} - \{E(y_{ijt}|Treat_j = 0, t = 1) - E(y_{ijt}|Treat_j = 0, t = 0)\} = \beta_2 \tag{1.4}$$

β_2, the primary estimate interest, measures how the LIVES program affects restaurants' hygiene scores in Orange County.

1.7 Test for Parallel Trends Assumption

The core assumption for the difference in differences approach is the parallel trends assumption, which requires that the inspection score trends for both the treated and control counties are the same in the absence of the policy. This assumption will be violated if the treatment is not independent of potential inspection score outcomes (Imbens, 2004).

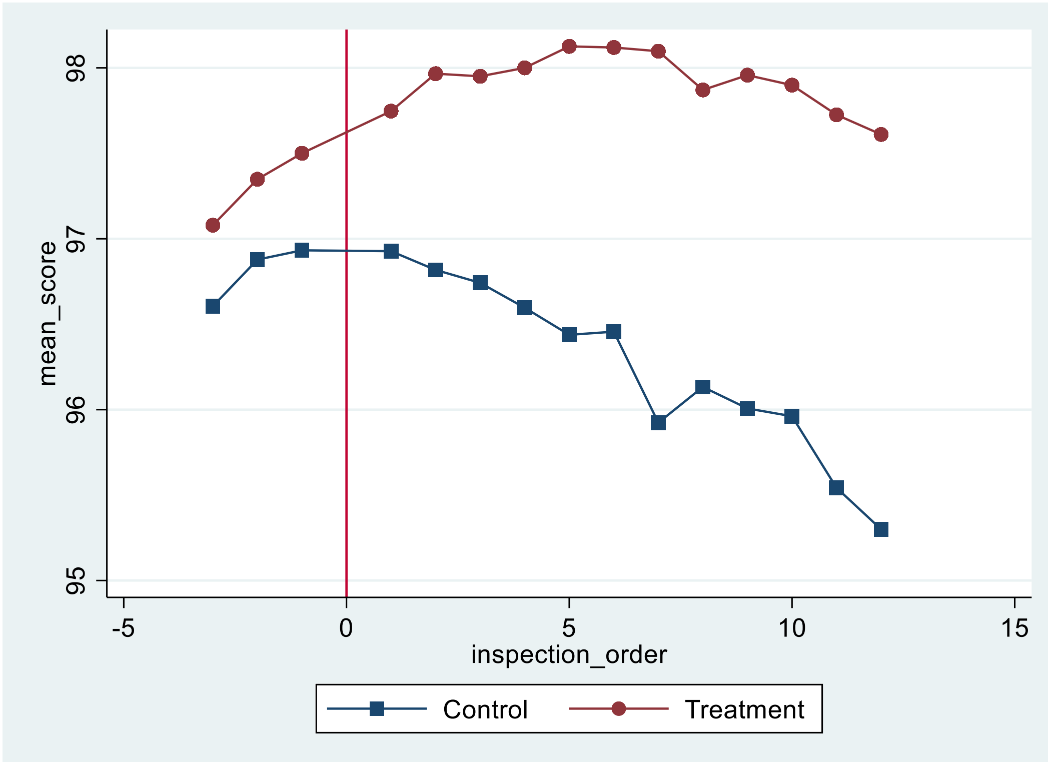

Figure 1.2: Mean inspection score before and after the LIVES program

A visual examination of the average inspection scores in both the treated and control groups, conducted before and after the policy's implementation, supports the parallel trends assumption. Figure 1.2 plots the inspection order on the x-axis and the mean inspection score on the y-axis. The first inspection following the policy's enactment is designated as 1, while the final inspection before the policy's introduction is marked as -1. Although not definitive, Figure 1.2 demonstrates that the trends in mean inspection scores ordered by inspection times are consistent before the policy's initiation.

To further test whether the parallel trends assumption holds, a placebo dummy was created for the two months before the program was implemented. Because the LIVES program was implemented in Orange County on September 16, 2014, the placebo dummy takes the value of zero on or before July 2014 and a value of one on August 2014. The placebo dummy takes the place of the $After$ variable in the robustness check and interacts with the $Treat$ variable. Table 1.3 presents the placebo test results. The estimates for the placebo dummy and placebo interaction with the $Treat$ variable are both insignificant, suggesting that the treated and the control group had the same trends before the change in the information disclosure policy.

Table 1.3: Test for Parallel Trends Assumption

Variable	Fixed effects
Placebo	0.329
	(0.186)
Treat*Placebo	-0.0842
	(0.182)
Constant	97.14***
	(0.00283)
Observations	5,862
R-squared	0.574
Business_id FE	YES
Year FE	YES
Month FE	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

1.8 Difference in Differences Results

Table 1.4 reports the main difference in differences results, with Orange County being the treated group and Durham County being the control group. I include business, month, and year fixed effects in the fixed effects, and the standard errors are clustered at the city level.

Table 1.4: Difference-in-Differences Results

Variable	Fixed effects
After	-0.370
	(0.328)
After*Treat	1.143***
	(0.209)
Constant	97.01***
	(0.263)
Observations	5,862
R-squared	0.584
Business_id FE	YES
Year FE	YES
Month FE	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The main coefficient estimate β_2 has a value of 1.143 and is statistically significant at p<0.1%, implying that the effect of joining the LIVES program, on average, improved Orange County restaurant inspection scores by 1.143 points. Such a result indicates a positive response from Orange County restaurants to the policy alteration, leading to enhancements in hygiene standards. While one may dismiss a single-point improvement in a 100-point inspection scale as inconsequential, it is important to consider the context. The average inspection score for Orange County prior to implementing the policy was 97.1322. Thus, the achievable enhancement was actually a maximum of 2.8678 points. With this perspective, the LIVES program's achievement of reducing hygiene violation scores by 1.143 points emerges as a significant 40% reduction in potential violation scores. The effectiveness of the LIVES program, as illustrated by this study, is considerably higher than the 12-14% reduction in health violations documented by Makofske (2020).

1.9 Empirical Specification - Geographic Regression Discontinuity Design

The geographic regression discontinuity (GRD) design leverages geographical boundaries and differences in policies across states or administrative units to measure the causal effect of a policy. While the difference in differences approach is widely used to examine the effect of a program in economics, the Geographic Regression Discontinuity is often used in political science and criminology when a geographic border defines the cutoff of the treated and control groups. Since the restaurants are locate close to each other, they operate under similar economic conditions, with the exception that restaurants on one side of the Orange-Durham border are subject to inspection results revealed on Yelp, while restaurants on the other side are not. A notable difference in hygiene scores between the treated and control groups would substantiate the hypothesis that the LIVES program has an effect on hygiene performance (Thistlewaite and Campbell, 1960). The validity of regression discontinuity relies on whether the treatment can be considered as randomly assigned to agents on either side of the threshold (Lee, 2008), and that agents cannot manipulate whether they are treated or not. In this case, it seems reasonable to assume that restaurants do not choose to locate at either side of the border to avoid or participate in the Lives program.

Restaurant inspection data come from Orange County and Durham County's websites. The most recent four inspection scores from September 2014 to February 2019 are used for each restaurant in Orange and Durham Counties after the LIVES program was enforced in September 2014. The dataset contains characteristics of restaurants, such as business identification number, name, street, and city. The dataset also includes inspection information such as inspection date and score. I convert restaurant addresses into latitudes and longitudes that represent the locations of the restaurants. In the Geographic Information System (GIS) software, these geographic coordinates of restaurants are plotted on the map to calculate the distance of these restaurants from the Orange-Durham County border.

For restaurants located within Orange County (treated county), the distances from the Orange-Durham County border are written as positive numbers, while the distances of Durham County restaurants to the border are recorded as negative numbers. Denoting D_j as the distance of a restaurant to the border, the dummy variable distinguishing restaurants in the treated vs. control groups can be defined as:

$$Treat_j = \begin{cases} 1 \ if \ D_j \geq 0, (Orange\ County) \\ 0 \ if \ D_j \leq 0, (Durham\ County) \end{cases} \tag{1.5}$$

Figure 1.3 offers a visual representation of the geographical distribution of restaurants across Orange and Durham Counties. The border between Orange and Durham Counties is a straight line, with restaurants in Orange County scattering in the center of the county and around the border, while restaurants in Durham County concentrate on the county's west side. The estimated populations in Orange and Durham Counties are 148,476 and 321,488, respectively (U.S. Census Bureau, 2019). This demographic difference may account for the higher restaurant number in Durham County compared to Orange County. In addition, some restaurants situated very close to the border appear to locate following a major interstate and state highway junctions in that area. This geographical feature significantly aids the identification strategy, in the sense that restaurants on either side of the border are similarly targeting road traffic, and the county border plays little role in determining location choices.

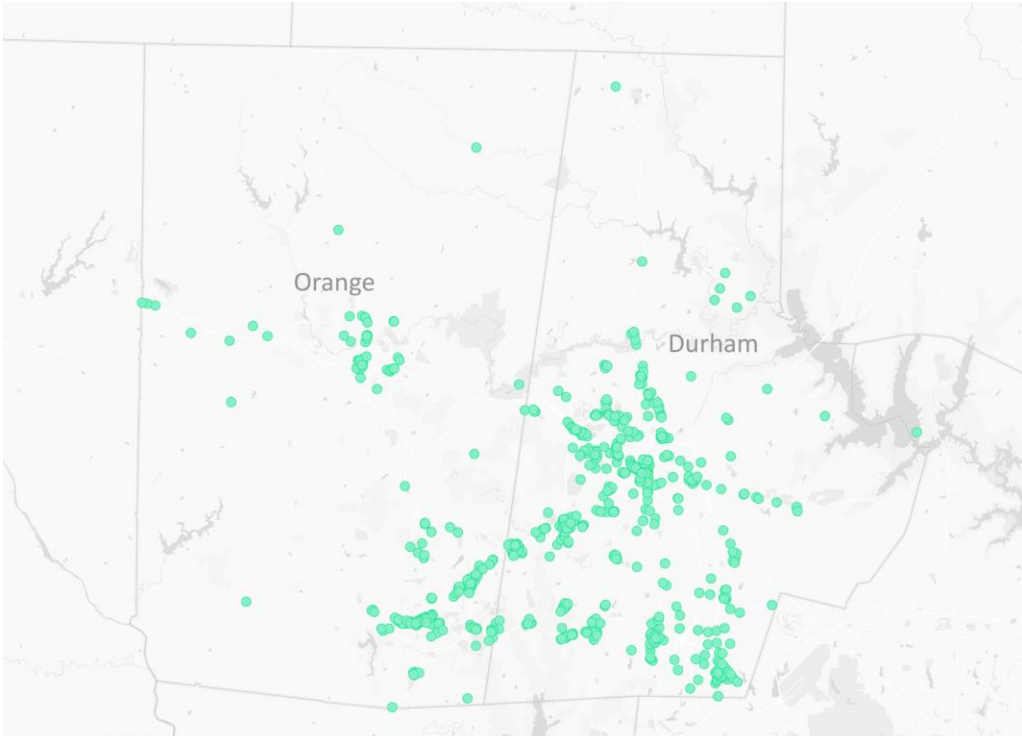

Figure 1.3: Restaurants in Orange and Durham County

Next, if h is the bandwidth defining a data neighborhood of restaurants close to the county border, and $\overline{y_t}$ $\overline{y_c}$ are the mean inspection score for restaurants located in the treated and control groups, then

$$\tau = \overline{y_t} - \overline{y_c} \; for \; -h_{opt} < D_j < h_{opt} \tag{1.6}$$

measures the (local) causal effect of the LIVES program on restaurant hygiene. The optimal bandwidth h_{opt} minimizes the asymptotic mean squared error of the treatment effect and its estimate (Li, 1987; Imbens and Kaalyanaraman, 2012).

Figure 1.4 is a density plot with restaurants' distances on the x-axis and their densities on the y-axis. The x-axis represents distances in miles, with Orange County's restaurants illustrated as distances greater than zero, and Durham County's restaurants represented as distances less than zero. According to this figure, I can observe a slight difference in the restaurant distributions between the two counties. Specifically, restaurants in Durham County (control) have a higher density compared to those in Orange County (treated).

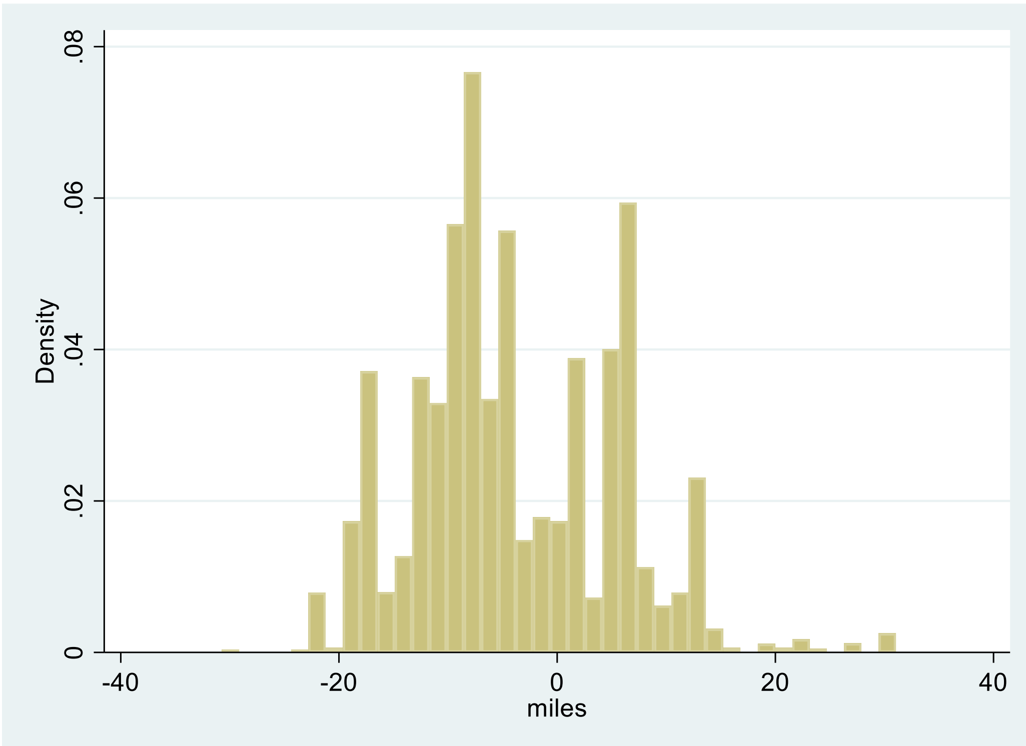

Figure 1.4: Histogram of restaurants in Orange and Durham Counties

Table 1.5 reports the manipulation testing with distance as a running variable. The manipulation test $T = -0.362$ with a p-value of 0.7174. This result shows there is no possibility of manipulation of the running variable.

Table 1.5: Regression Discontinuity Manipulation Test

Running Variable: Miles	T	P>|T|
Robust	-0.362	0.7174

Figure 1.5 is generated using the regression discontinuity manipulation test (McCrary, 2008) detailed in Table 1.5. In the plot, I can see no discontinuity near the threshold where miles

are equal to zero. This observation suggests that restaurants are not intentionally locating themselves on one side of the border or another.

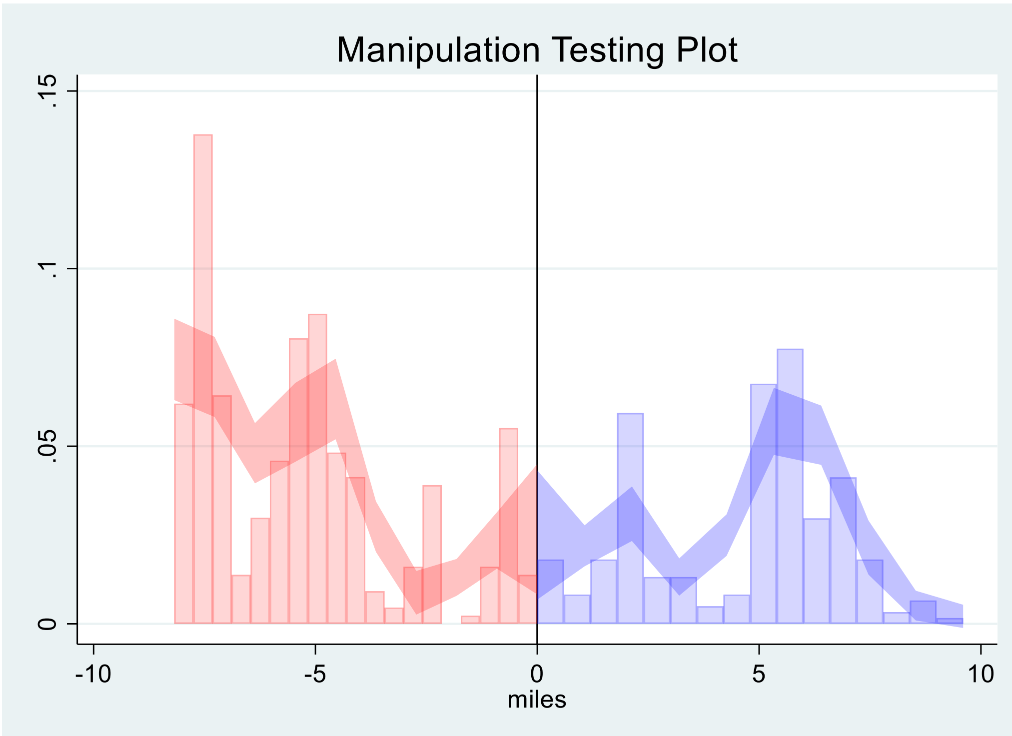

Figure 1.5: Restaurant manipulation testing plot

1.10 Geographic Regression Discontinuity Results

I apply two methods to calculate the optimal bandwidth: the Imbens and Kalyanaraman (IK) method and the Calonico, Cattaneo, and Titunik (CCT) method. Imbens and Kalyanaraman (2012) propose an asymptotically optimal bandwidth that minimizes the first-order approximation of the mean squared error of the treatment parameter and treatment parameter estimate. Calonico, Cattaneo, and Titiunik (2014) propose the bias-corrected estimator by estimating the bias in the distributional approximation and then deducting it from the point estimate.

Table 1.6 reports the conventional coefficient estimates from two different approaches: IK and CCT. A conventional estimate is the point estimate of the local treatment effect that minimizes the mean squared error between the effect parameter and its estimate. The estimates from the IK and CCT methods are both statistically significant at a 5% significance level.

Table 1.6: Sharp R.D. Estimates Using Local Polynomial Regression

	IK	CCT
Conventional coefficient	0.24401*	0.34514***
Conventional Std. Err.	0.14343	0.11774
Number of Observations	9,522	9,522
Bandwidth (miles)	4.982	7.036
Kernel Type	Triangular	Triangular

*** p<0.01, ** p<0.05, * p<0.1

The estimates from the GRD approach, 0.244 (IK estimate) and 0.345 (CCT estimate), are positive and significant, but much smaller than the difference in differences estimate (1.143).

1.11 Robustness Check

To test the sensitivity of the findings from GRD, I perform different robustness checks. First, I re-estimate the GRD model using different bandwidths and plot the variations in effect size as a function of these bandwidth changes. This plot is visually represented in Figure 1.6, which illustrates the impact of the LIVES program on restaurant hygiene quality as the bandwidth varies from 4 to 10 miles. I purposefully excluded smaller bandwidths ranging from 1 to 3 miles from the graph, as these estimates were discovered to be biased. As bandwidth approaches the optimal value of 7 miles given by the CCT method, the effect of the policy stabilizes. This stabilization lends further support to the primary findings presented in Table 1.6.

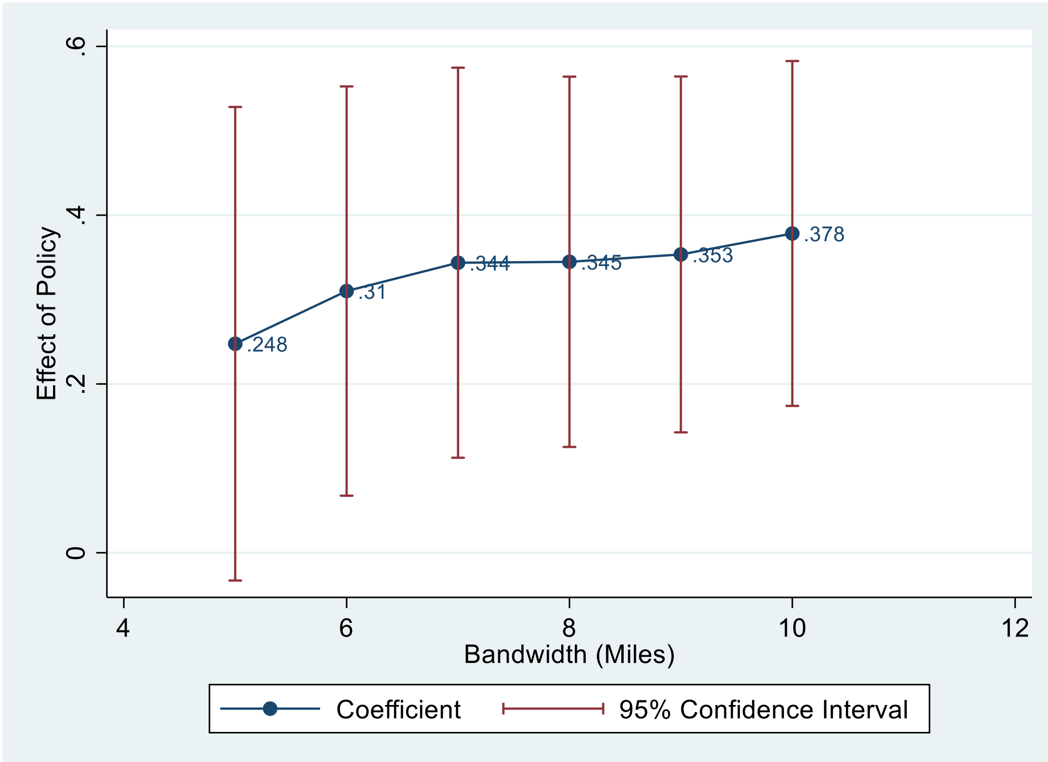

Figure 1.6: Estimating the Effect of the LIVES Program with Different Bandwidths

Second, I re-estimate the GRD model with a different outcome variable. Specifically, I use the probability of a restaurant being Mexican as the dependent variable. Variable *Mexican* is equal to 1 if a restaurant is Mexican and 0 otherwise.

Table 1.7: GRD Assumption Test with Mexican as Outcome Variable

Variable	(1) 4 Inspections after policy	(2) 3 Inspections after policy	(3) 2 Inspections after policy	(4) 1 Inspection after policy
Conventional coefficient	0.02304	0.03905	0.02822	0.0206
Conventional Std. Err.	0.01873	0.03161	0.03873	0.06435
Bias-corrected coeff.	0.02997	0.04817	0.03642	0.02748
Number of Observations	3,813	2,929	1,995	1,011
Bandwidth (miles)	6.49	5.738	6.451	7.002
Kernel Type	Triangular	Triangular	Triangular	Triangular

*** p<0.01, ** p<0.05, * p<0.1

Table 1.7 reports the GRD results with *Mexican* as the outcome variable. Column (1) in Table 1.7 presents the GRD placebo test results using up to four inspections per restaurant after the policy is implemented. Similarly, Columns (2) to (4) show the results with different numbers of inspections after the policy. All the conventional and bias-corrected coefficients are insignificant, which means that the GRD effect of treatment does not affect the probability of a restaurant being Mexican.

Third, I run a pretreatment placebo test using the inspection score as the outcome variable.

Table 1.8: GRD Placebo Test with Pretreatment Data

Variable	(1) 2 Inspections prior to policy	(2) 1 Inspection prior to policy
Conventional coefficient	0.05857	0.02509
Conventional Std. Err.	0.50921	0.70952
Bias-corrected	-0.01654	-0.06388
Number of Observations	1,271	655
Bandwidth (miles)	4.551	4.724
Kernel Type	Triangular	Triangular

*** p<0.01, ** p<0.05, * p<0.1

Table 1.8 reports the placebo test estimates of the effect of the policy using only pretreatment data. Neither the conventional nor the bias-corrected coefficients are significant. In addition, all coefficients are close to zero. This evidence shows there is no treatment effect prior to the policy.

1.12 Discussion

The Geographic Regression Discontinuity (GRD) methodology offers an alternative lens to evaluate the causal impact of the LIVES program. Although GRD results appear smaller than the Difference in Differences (DID) estimates, GRD results lend credibility to the DID estimates. The GRD is specifically designed to calculate the local average treatment effect for restaurants within a defined bandwidth. Conversely, the DID methodology focuses on the average treatment effect of the LIVES program on a treated county as a whole. They provide different perspectives on estimating the causal effects of the policy.

Both the DID and the GRD approaches provide compelling evidence that implementing the LIVES program improves restaurant inspection scores in the treated group. This finding aligns with conclusions drawn in prior research. However, making a direct comparison of the magnitude of the results between this study and prior ones may be unreasonable, given the variability in inspection criteria across states and, occasionally, across counties. For example, Jin and Leslie (2003) conclude that the mandatory disclosure of restaurant hygiene through onsite grade cards improved inspection scores by 4.4 points in Los Angeles County. Although both Los Angeles and Orange Counties use a 100-point scale to denote perfect cleanliness, disparities in the distribution of inspection items and their respective weights render a comparison of improvements in hygiene quality impractical.

This study also supports Makofske's (2020) research, which examines the effect of the Louisville-Yelp partnership on restaurant hygiene. Makofske (2020) finds that posting inspection reports of Louisville restaurants on Yelp induces restaurants to reduce health violation scores by 12-14%, with a health violation score being the residual from subtracting the inspection score from 100. Even though our effect size estimates differ, both studies confirm the positive effect of disclosing inspection on Yelp on restaurant hygiene quality. Considered together, these empirical studies support the theory that reducing information asymmetry on quality between consumers and producers will prompt producers to improve the quality of their products.

A central question relates to what motivates restaurants to improve quality following public disclosure of inspection information. Jin and Leslie (2003) suggest that demand at restaurants with good hygiene may increase while demand at restaurants with bad hygiene may decrease. Consequently, prices may rise in restaurants with high inspection scores while potentially declining in those receiving lower scores. In the context of this study, I anticipate restaurant prices to remain relatively constant as this analysis focuses on short-term impacts. The driving force for restaurants to upgrade their hygiene standards is the shift in demand prompted by consumers who are informed via Yelp following the disclosure of inspection information.

1.13 Conclusion

This study investigates the impact of making restaurant inspection information public on Yelp, focusing on its influence on the overall hygiene quality of restaurants. Economic theory suggests that the transparency from such disclosure on Yelp would incentivize restaurants to improve hygiene quality. The empirical data collected supports this hypothesis, indicating an improvement in the inspection scores of restaurants in Orange County after the local government began to publicize this information via Yelp's LIVES program.

Leveraging a substantial dataset, this study uses two separate empirical approaches to examine the effect of the LIVES program on restaurant hygiene. Both approaches support the conclusion that the LIVES program has exerted a positive impact on restaurant hygiene. This study offers new evidence to support the argument that providing more information about product quality to consumers improves product quality.

The findings of this study should motivate North Carolina counties, which have shown reluctance towards the LIVES program, to reconsider their stance. The costs of complying with the program are small compared to the enormous public costs associated with foodborne illnesses — amounting to over $15.6 billion in 2014, causing the annual loss of 2,377 American lives (Flynn, 2014). Considering these significant implications, the expenses incurred for engaging officers to structure and adapt the inspection data into the format required by the LIVES program appear to be a relatively trivial investment.

The LIVES program facilitates consumers' access to government restaurant inspection data by making this information readily available on Yelp. As many consumers already rely on Yelp for identifying and reviewing restaurants, they can easily locate the inspection information without having to navigate through a government website. The familiarity of Yelp not only cuts down the time spent on restaurant search but also boosts the chances of consumers utilizing this valuable data. This research, therefore, reinforces the merits of public initiatives aimed at making crucial government data more accessible to the general public.

References

Akerlof, G. A. (1970). The Market for "Lemons": Quality Uncertainty and the Market Mechanism. The Quarterly Journal of Economics, 84(No.3), 488–500.

Aksoydan, E. (2007). Hygiene Factors Influencing Customers' Choice of Dining-out Units: Findings from a Study of University Academic Staff. *Journal of Food Safety*, 27(3), 300–316.

Angrist, J. D.; Pischke, J. S. (2009). Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press.

Beaulieu, N. D. (2002). Quality information and consumer health plan choices. *Journal of Health Economics*, 21(1), 43–63.

Bennear, L. S., & Olmstead, S. M. (2008). The impacts of the "right to know": Information disclosure and the violation of drinking water standards. *Journal of Environmental Economics and Management*, 56(2), 117–130.

Bundorf, M. K., Chun, N., Goda, G. S., & Kessler, D. P. (2009). Do markets respond to quality information? The case of fertility clinics. *Journal of Health Economics*, 28(3), 718–727.

Calonico, S., Cattaneo, M. D., & Titiunik, R. (2014). Robust Nonparametric Confidence Intervals for Regression Discontinuity Designs. *Econometrica*, 82(6), 2295–2326.

Dafny, L., & Dranove, D. (2008). Do report cards tell consumers anything they don't already know? The case of Medicare HMOs. *The RAND Journal of Economics*, 39(3), 790–821.

Douglas Anna. (2017) What did restaurant inspectors find in Charlotte kitchens? Yelp has the answer. *The Charlotte Observer*. Retrieved from https://www.charlotteobserver.com/news/business/article153401854.html

Dranove, D., Kessler, D., McClellan, M., & Satterthwaite, M. (2013). Is More Information Better? The Effects of "Report Cards" on Health Care Providers. *Journal of Political Economy*, 34.

Dunning, Thad. (2012). Natural Experiments in the Social Sciences: A Design-Based Approach. Cambridge University Press.

FDA. (2017). Food Code 2017. Retrieved from https://www.fda.gov/food/fda-food-code/food-code-2017

FDA. (2020). Adoption of the FDA Food Code by State and Territorial Agencies Responsible for the Oversight of Restaurants and Retail Food Stores 2017. Retrieved from https://www.fda.gov/media/107543/download

Lu, Susan Feng. (2012). Multitasking, Information Disclosure, and Product Quality: Evidence from Nursing Homes. *Journal of Economics & Management Strategy*, 21(3), 673–705.

Flynn Dan. (2014). USDA: U.S. Foodborne Illnesses Cost More Than $15.6 Billion Annually. *Food Safety News*. Retrieved from https://www.foodsafetynews.com/2014/10/foodborne-illnesses-cost-usa-15-6-billion-annually/

Hastings, J. S., & Weinstein, J. M. (2008). Information, School Choice, and Academic Achievement: Evidence from Two Experiments. *The Quarterly Journal of Economics*, 1373–1414.

Henson, S., Majowicz, S., Masakure, O., Sockett, P., Jones, A., Hart, Carr, D., Knowles, L. (2006). Consumer assessment of the safety of restaurants: The role of inspection notices and other information cues. *Journal of Food Safety*, 26(4), 275–301.

Hoffman, Sandra. (2011). U.S. Food Safety Policy Enters a New Era. Retrieved from https://www.ers.usda.gov/amber-waves/2011/december/us-food-safety-policy/

Iacus, S.M., G. King, & G. Porro. (2011). Causal Inference Without Balance Checking: Coarsened Exact Matching. *Political Analysis* 20(1): 1-24.

Imbens, G. W. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and statistics*, 86(1), 4-29.

Imbens, G., & Kalyanaraman, K. (2012). Optimal Bandwidth Choice for the Regression Discontinuity Estimator. *The Review of Economic Studies*, 79(3), 933–959.

Jin, G. Z., & Leslie, P. (2003). The Effect of Information on Product Quality: Evidence from Restaurant Hygiene Grade Cards. *The Quarterly Journal of Economics*, 118(2), 409–451.

Jin, G. Z., & Leslie, P. (2009). Reputational Incentives for Restaurant Hygiene. *American Economic Journal: Microeconomics*, 1(1), 237–267.

Jin, G. Z., & Sorensen, A. T. (2006). Information and consumer choice: The value of publicized health plan ratings. *Journal of Health Economics*, 25(2), 248–275.

Kang, D. (2015). Effect of Information on Consumer Perception: Evidence from Restaurant Hygiene Grade Cards in New York City. *AAWE Working Paper*, (No.183).

Lee (2008). Randomized Experiments from Non-random Selection in U.S. House Elections. Journal of Econometrics. 142 (2): 675–697.

Li Ker-Chau. (1987). Asymptotic Optimality for C_p, C_L, Cross-Validation and Generalized Cross-Validation: Discrete Index Set. *The Annals of Statistics*. 1987, Vol. 15, No. 3, 958-975.

Los Angeles County. (2023). Grading and Posting Requirements for Retail Food Facilities. Retrieved at: http://publichealth.lacounty.gov/eh/inspection/grading-posting-requirements-retail-food-facilities.html

Lu, S. F. (2012). Multitasking, Information Disclosure, and Product Quality: Evidence from Nursing Homes. *Journal of Economics & Management Strategy*, 21(3), 673–705.

Luca, Michael. (2016). "Reviews, Reputation, and Revenue: The Case of Yelp. Com." *Working Paper* 12-016.

Makofske, M. P. (2020). The Effect of Information Salience on Product Quality: Louisville Restaurant Hygiene and Yelp.com. *The Journal of Industrial Economics*, 68(1), 52–92. https://doi.org/10.1111/joie.12214

McCrary, Justin. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics* 142 698-714.

Pope, D. G. (2006). Reacting to Rankings: Evidence from “America’s Best Hospitals and Colleges.” Job Market Paper.

Powers, N., Blackman, A., Lyon, T. P., & Narain, U. (2008). Does Disclosure Reduce Pollution? Evidence from India’s Green Rating Project. *Resources for the Future* D.P. 08-38.

ReviewTrackers. (2020). Online Reviews Statistics and Trends: A Report by ReviewTrackers. Retrieved January 8, 2022, from https://www.reviewtrackers.com/reports/online-reviews-survey/

Shueh, Jason. (2015). Yelp, Socrata Partner to Make Restaurant Inspections Public. *Government Technology*. Retrieved from https://www.govtech.com/data/Yelp-Socrata-Partner-to-Make-Restaurant-Inspections-Public.html

Stigler, G. J. (1961). The Economics of Information. *Journal of Political Economy*, Vol. 69(No.3), 213–225.

Thistlethwaite, D. L., & Campbell, D. T. (1960). Regression-discontinuity analysis: An alternative to the ex post facto experiment. *Journal of Educational Psychology*, 51(6), 309–317.

U.S. Census Bureau. (2019). County Population Totals: 2010-2019. Census.Gov. Retrieved January 8, 2022, from https://www.census.gov/data/tables/time-series/demo/popest/2010s-counties-total.html

Wedig, G. J., & Tai-Seale, M. (2002). The effect of report cards on consumer choice in the health insurance market. *Journal of Health Economics*, 21(6), 1031–1048.

Yelp. (2018). Bringing Restaurant Hygiene Scores to Yelp Pages Everywhere. Retrieved from https://blog.yelp.com/2018/07/lives-national

Yelp. (2018). Local Inspector Value-Entry Specification (LIVES). Retrieved from https://www.yelp.com/healthscores

2 THE IMPACT OF ONLINE REVIEWS ON RESTAURANT WAGES: EVIDENCE FROM COLORADO

2.1 Introduction

Consumer reviews express satisfaction or dissatisfaction after using or consuming experience goods or services. These are goods or services—such as restaurant meals, movies, or books—that can only be fully evaluated after they have been consumed. As Nelson (1970, p327) concludes, “The recommendations of others will be used more for purchases of experience goods than search goods.” Therefore, these reviews provide valuable personal insights to potential consumers before purchasing.

Before the prevalence of the internet, expert reviews helped consumers decide which experience good to choose. For example, movie critics help consumers decide which films to watch through television shows and newspaper commentaries (Reinstein and Snyder, 2005). However, the relatively limited media avenues for providing such expert opinions of that era limited the crowd-sourced publication of opinions that are so common and easily accessed today. With the rapid development of information technology and social media, expert opinions can be broadly distributed and successfully monetized to appear at scale. Consumers today increasingly utilize online reviews from both expert and crowd-sourced opinions that are freely available at the convenience of consumers.

As the volume and accessibility of online reviews for experience goods continue to grow, they effectively become non-excludable. Consumers can freely access these reviews without any cost. Positive reviews for a restaurant, for instance, may drive up demand, potentially leading to overcrowding. Given the physical constraints of restaurant space, the supply cannot readily expand to meet this increased demand.

It is well established that expert reviews, social learning, and consumer reviews affect demand for a broad array of experience goods. These goods include wine (Hilger et al., 2011; Friberg and Grönqvist, 2012), movies (Reinstein and Snyder, 2005; Moretti, 2011), books (Chevalier and Mayzlin, 2006), and restaurant meals (Cai et al., 2009; Anderson and Magruder, 2012; Luca, 2011). While many empirical economists have studied how online reviews affect the sales revenues from or demand for the product/service (e.g., Chevalier and Mayzlin, 2006; Anderson and Magruder, 2012), few have examined whether this effect drives producers to pay more for their workers. This paper seeks to identify and quantify such an effect.

2.2 Literature Review

Several researchers have studied the effect of expert reviews on consumer demand for experience goods. Reinstein and Snyder (2005) study the effect of the two renowned movie critics—Siskel and Ebert—on consumer demand for movies. Their findings revealed that positive reviews significantly increased the number of patrons, thus boosting movie revenues. Using a randomized controlled experiment, Hilger et al. (2011) find that expert reviews improve overall wine sales by 25%. This effect is bi-directional: high-scoring expert reviews increase sales, while low-scoring reviews lead to a decrease. In another study, Friberg and Grönqvist (2012) examine the influence of expert reviews on wine demand in Sweden, using weekly sales data from 2002 to 2007. They corroborate the positive effect of favorable reviews on wine sales, yet discover that unfavorable reviews do not have a significant impact.

Social learning significantly influences consumer decisions regarding experience goods. For instance, Cai et al. (2009) find that when customers are informed about the top five dishes at a restaurant, they spend 13 to 18 percent more. In a different study, Duflo and Saez (2003) examine average participation rates across various groups, showing that social learning impacts employees' decisions about retirement. Similarly, Moretti (2011), using a different methodology but arriving at a comparable conclusion, finds that employees' health plan choices are significantly influenced by the decisions of their coworkers.

Alongside expert reviews and social learning, online reviews are another critical source of product quality information that influences consumer decision-making (Anderson and Magruder, 2012). Chevalier and Mayzlin (2006) investigate the impact of online consumer reviews on book sales at Amazon.com and Barnesandnoble.com. Their findings suggest that positive reviews drive an increase in book sales. Using a regression discontinuity design, Anderson and Magruder (2012) study the effect of positive consumer reviews on Yelp.com on restaurant demand. They find that a half-star rating improvement on a five-star scale prompts a 19% rise in consumer reservations. In a similar vein, Luca (2011) applies a regression discontinuity method to analyze the impact of consumer reviews on Yelp.com on restaurant revenues. His research concludes that a one-star rating increase correlates with a 5-9 percent revenue boost.

2.3 Background

To study the effect of consumer reviews on restaurant wages, I select restaurants in Colorado as the study sample. The restaurant industry in Colorado plays a crucial role in the state's economy. As reported by the Colorado Restaurant Association (2021), there were around 11,800 food establishments in Colorado in 2019, with independent restaurants accounting for more than 75% of this total, the remainder being chain restaurants. With a workforce of 285,000, representing about 10% of Colorado's total employment, the industry generated an estimated $13.9 billion in revenue in 2018.

There are typically three compensation methods in the restaurant industry. Front-of-the-house positions, including host/hostess, busser, server, and bartender roles, earn an hourly wage supplemented by tips. Back-of-the-house roles, such as dishwashers and line cooks, receive an hourly wage. Managers and chefs, on the other hand, are paid annual salaries. For front-of-the-house staff in Colorado, wages are regulated by the tipped employee minimum wage, set by the Colorado Department of Labor and Employment (2021). This rate was \$7.18 per hour in 2018. In contrast, back-of-the-house employees are compensated at the state minimum wage, typically higher than the tipped employee minimum wage. In 2018, this rate was \$10.20 per hour in Colorado. If a tipped employee's total earnings (tips plus the employer's hourly rate multiplied by hours worked) fall short of the state minimum wage multiplied by hours worked, the employer is required to make up the difference.

Table 2.1 presents the state-level and federal-level minimum wages from 2006 to 2019, as well as the minimum wage for tipped employees in Colorado during the same period. Except for a slight decrease in 2010, Colorado's minimum wage consistently rose from 2006 to 2019. During this time, the minimum wage for tipped employees in Colorado increased steadily, growing from \$2.13 in 2006 to \$8.08 in 2019. Despite the rapid increase of Colorado's minimum wage—reaching \$15.87 by 2022—the federal minimum wage has remained unchanged at \$7.25 since 2009, marking an 11-year period of stagnation.

Table 2.1: Minimum wages from 2006 to 2019

Effective Date	CO Minimum Wage	CO Tipped Employee Minimum Wage	Federal Minimum Wage
1/1/2019	$11.10	$8.08	$7.25
1/1/2018	$10.20	$7.18	$7.25
1/1/2017	$9.30	$6.28	$7.25
1/1/2016	$8.31	$5.29	$7.25
1/1/2015	$8.23	$5.21	$7.25
1/1/2014	$8.00	$4.98	$7.25
1/1/2013	$7.78	$4.76	$7.25
1/1/2012	$7.64	$4.62	$7.25
1/1/2011	$7.36	$4.34	$7.25
1/1/2010	$7.24	$4.22	$7.25
1/1/2009	$7.28	$4.26	$7.25
1/1/2008	$7.02	$4.26	$6.55
1/1/2007	$6.85	$3.83	$5.85
1/1/2006	$5.15	$2.13	$5.15

Source: Department of Labor (2023), Colorado Department of Labor and Employment (2021)

I believe that a causal relationship may exist between online consumer reviews and restaurant wages for three key reasons. Firstly, established research (e.g., Luca, 2011; Anderson and Magruder, 2012) has identified a causal impact of online consumer reviews, particularly from Yelp.com, on consumer demand, demonstrating that higher review ratings spur increased demand. Secondly, assuming this causal relationship applies to this study, I would expect a one-star increase in Yelp rating to correspondingly boost consumer demand for restaurant meals. Lastly, although certain restaurant staff members, like managers, may not be directly impacted by fluctuations in demand, others, such as waiters and bartenders, depend on tips and the number of hours they work. These income sources are closely tied to consumer demand at the restaurant.

2.4 Data

This study employs two datasets to study the effect of online consumer reviews on restaurant workers' wages. The first dataset is consumer review data downloaded from

Yelp.com, and the second dataset is Quarterly Census Employment and Wages (QCEW) data from the U.S. Bureau of Labor Statistics.

Consumers can post reviews by first creating an account using a valid email address. After registration, they can search for a restaurant on Yelp's platform and select the "Write a Review" option. The review interface presents five grey stars that users can click to reflect their rating. Each star corresponds to a different evaluation: one star means "Not good", two stars suggest it "Could've been better", three stars denote "OK", four stars express "Good", and five stars indicate a "Great" experience. Additionally, consumers have the ability to enrich their reviews by attaching relevant photographs.

This Yelp review dataset incorporates a collection of variables providing detailed descriptions of the restaurants spanning from the first quarter of 2004 to the fourth quarter of 2018. It encompasses numerous variables, such as the restaurant's name, location, total review count, star rating, price range, and cuisine type (e.g., Mexican). Each observation in the dataset corresponds to a restaurant-quarter-year unit. This data provides detailed information about each restaurant.

The QCEW data covers the period from the first quarter of 2008 to the third quarter of 2018 and includes information on business characteristics, such as name, address, phone number, as well as quarterly data on total wages, taxable wages, contributions, and monthly employment for Colorado businesses. This data is separable down to the individual business level.

I merge the Yelp review data with the QCEW data by business name and phone number. The first step in the data-cleaning process is to drop the unmatched observations. Second, I identify those restaurants that reported their total wages as zero or missing values and drop these restaurants. Third, I check whether there is a restaurant with monthly employment of zero or missing values to identify the outliers that have mean wages greater than the 99th percentile. Lastly, I drop restaurants with mean wages greater than the 99th percentile or less than the 1st percentile. After these steps, the sample comprises 4,451 restaurants in the final dataset available for analysis.

Table 2.2 reports the summary statistics I use in the analysis. The mean quarterly wage for all restaurants in the sample is \$4190.06. Equivalently, the monthly mean wage for restaurants is \$1396.69.

Table 2.2: Summary statistics of the whole sample

Variable	count	mean	std	min	0.25	0.50	0.75	max
meanwage	115836	4190.06	1458.36	1176.69	3137.58	3983.11	5034.80	9353.17
meanstar	65255	3.46	1.13	1.00	3.00	3.71	4.27	5.00
cum_meanstar	92200	3.41	0.84	1.00	3.00	3.52	4.00	5.00
cum_quarterreviews	115836	33.83	82.61	0.00	1.00	8.00	33.00	2697.00
pricerange2 ($$)	115836	0.43	0.49	0.00	0.00	0.00	1.00	1.00
pricerange3 ($$$)	115836	0.02	0.15	0.00	0.00	0.00	0.00	1.00
pricerange4 ($$$$)	115836	0.00	0.05	0.00	0.00	0.00	0.00	1.00

The variable *meanstar* is calculated using equation (2.1) for each quarter.

$$meanstar = \frac{onestar*1 + twostar*2 + threestar*3 + fourstar*4 + fivestar*5}{onestar + twostar + threestar + fourstar + fivestar} \tag{2.1}$$

In equation (2.1), variable *onestar* is the number of one-star ratings a restaurant received in a certain quarter. Variable *twostar* is the count of the two-star ratings a restaurant received in a certain quarter. Variables *threestar*, *fourstar*, and *fivestar* are defined analogously. The variable *meanstar* is the weighted average calculated for each quarter by summing up the products of each star rating and its respective weight and then dividing by the total number of ratings received.

Cumulative mean star rating (*cum_meanstar*) is calculated similarly to *meanstar*, but rather than considering ratings in a certain quarter, the cumulative mean star rating considers all ratings given up until a specified point in time. The cumulative quarter reviews (*cum_quarterreviews*) tally the cumulative sum of reviews for a restaurant starting from its first review. The dataset is unbalanced because restaurants received their first review in different year-quarter combinations. I carefully checked the data to ensure accurate tallying of cumulative reviews, even if a restaurant shuts down.

Additionally, the dataset classifies restaurants into four different pricing categories: "$" represents a meal under $10, "$$" denotes a price range of $11-$30, "$$$" equates to $31-$60, and "$$$$" implies a meal price exceeding $61. The dataset encompasses 2275 restaurants in the "$" category, 2134 in the" "category, 112 in the "$$$" category, and 14 in the "$$$$" category.

2.5 Empirical Specifications

I use fixed effects models to study the effect of consumer reviews on restaurant wages, controlling for possible observable and unobservable variables that affect demand for restaurant meals. In particular, I run the following reduced form fixed effects model using the cleaned data from the previous section,

$$W_{isty} = \beta_0 + \beta_1 M_{isty} + \beta_2 R_{isty} + \beta_3 W_{isy(t-1)} + \alpha_i + \delta_s + \gamma_t + \theta_y + \varepsilon_{isty} \tag{2.2}$$

where W_{isty} is the mean wage of restaurant i distributed to its employees in city s in quarter t in year y. It is calculated as the total quarterly wage divided by the mean employment in a restaurant i. Specifically, I calculate the mean employment using the sum of monthly employment to divide by the observed months. M_{isty} is the mean star rating for restaurant i in city s in quarter t in year y on Yelp.com. R_{isty} is the count of total quarter reviews for restaurant i in city s in quarter t in year y. $W_{isy(t-1)}$ is added to the model to control for autocorrelation.

α_i is the restaurant level fixed effect controlling restaurant characteristics that are time-invariant and likely to affect restaurant wages. δ_s is the time-invariant city fixed effect controlling for both observed and unobserved city-level characteristics (such as legislation) that may affect restaurant wages. γ_t captures the quarterly time-invariant factors (such as seasonality) that can affect restaurant wages. θ_y is the year fixed effect that controls year-specific factors that could affect restaurant wages. ε_{isty} is the error term that contains information on the unobservable factors.

Despite providing useful information for examining the effect of reviews on restaurant wages in the same quarter, equation (2.2) does not provide insight into how reviews from previous quarters could affect restaurant wages in the current quarter. To differentiate this, I gradually add cumulative mean star rating and cumulative reviews. If the effect from previous quarters does not affect the effect from the current quarter, then adding these variables should not change the outcome of the results.

To investigate whether previous reviews affect the current wage in a restaurant, I estimate the following equations:

$$W_{isty} = \beta_0 + \beta_1 M_{isty} + \beta_2 M\_cum_{isty} + \beta_3 R_{isty} + \beta_4 W_{isy(t-1)} + \alpha_i + \delta_s + \gamma_t + \theta_y + \varepsilon_{isty} \quad (2.3)$$

$$W_{isty} = \beta_0 + \beta_1 M_{isty} + \beta_2 R_{isty} + \beta_3 R\_cum_{isty} + \beta_4 W_{isy(t-1)} + \alpha_i + \delta_s + \gamma_t + \theta_y + \varepsilon_{isty} \quad (2.4)$$

$$W_{isty} = \beta_0 + \beta_1 M\_cum_{isty} + \beta_2 R_{isty} + \beta_3 R\_cum_{isty} + \beta_4 W_{isy(t-1)} + \alpha_i + \delta_s + \gamma_t + \theta_y + \varepsilon_{isty} \quad (2.5)$$

$$W_{isty} = \beta_0 + \beta_1 M_{isty} + \beta_2 M\_cum_{isty} + \beta_3 R_{isty} + \beta_4 R\_cum_{isty} + \beta_5 W_{isy(t-1)} + \alpha_i + \delta_s + \gamma_t + \theta_y + \varepsilon_{isty} \quad (2.6)$$

where M_cum_{isty} represents the cumulative mean star rating of a restaurant i. R_cum_{isty} is the cumulative count of the reviews a restaurant receives from the first review.

Table 2.3 presents the estimated outcomes of five unique specifications of the baseline models. Initially, before I account for the prior information of reviews, the estimate for variable *meanstar* within the current quarter is significant. The coefficient for the review count (*totalquarterreviews*) within the same quarter is of a larger magnitude relative to the coefficient of *meanstar*, suggesting a more pronounced impact on consumer demand based on the number of reviews within a given quarter.

As I move to Column (2), I include the cumulative mean star rating (*cum_meanstar*) from past quarters. The significance of cumulative mean star rating indicates its importance in influencing consumer demand, as opposed to the mean star rating (*meanstar*) of the current quarter. This observation is further corroborated by the results detailed in Columns (4) and (5).

From Columns (3) to (5), I can conclude that cumulative mean star rating (*cum_meanstar*) and the reviews in the current quarter (*totalquarterreviews*) are the determinant factors in shaping consumer demand, and consumers value the sum of reviews in the current quarter more than in previous quarters.

Table 2.3: Estimation Results from Fixed Effects Models

Variable	(1) Baseline Model 1	(2) Baseline Model 2	(3) Baseline Model 3	(4) Baseline Model 4	(5) Baseline Model 5
meanstar	4.267	-2.655	3.353		-2.913
	(4.426)	(4.234)	(4.302)		(4.185)
cum_meanstar		43.78***		35.16***	39.70***
		(12.41)		(13.10)	(12.16)
totalquarterreviews	20.16***	20.02***	16.32***	16.25***	16.24***
	(5.900)	(5.894)	(5.948)	(5.946)	(5.940)
cum_totalquarterreviews			0.567***	0.559***	0.559***
			(0.104)	(0.103)	(0.104)
y_lag1	0.306***	0.306***	0.301***	0.301***	0.301***
	(0.0369)	(0.0369)	(0.0362)	(0.0363)	(0.0362)
Constant	3,131***	3,004***	3,142***	3,032***	3,026***
	(151.7)	(166.8)	(145.9)	(162.6)	(158.7)
Observations	63,230	63,230	63,230	63,230	63,230
R-squared	0.766	0.766	0.766	0.766	0.766
City FE	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

*** p<0.01, ** p<0.05, * p<0.1

2.6 Identification Strategy

One potential threat to the identification is the concern that reverse causality might play a role in the models. To test this possibility, I implement fixed effects models similar to the aforementioned specifications but also include lags of up to five quarters. If the mean star rating from previous quarters significantly affects the mean wage in the current quarter, then there is no reverse causality because what happened now can not affect what happened in the past. The results from Table 2.4 show that the lagged mean star variables significantly affect the mean wage in the current quarter. However, it is not logically possible for the current quarterly wage to affect past quarterly mean star ratings.

Table 2.4: Estimation Results from Fixed Effects Models with lags of independent variables

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
meanstar	-3.052	-1.546	0.566	1.765	-1.083	-2.005
	(7.710)	(7.566)	(7.830)	(7.708)	(7.811)	(7.945)
lag1q_meanstar		9.585	11.76*	12.79**	10.23	9.340
		(6.289)	(6.277)	(6.287)	(6.458)	(6.727)
lag2q_meanstar			13.62**	14.74***	12.33**	11.52**
			(5.435)	(5.056)	(5.370)	(5.532)
lag3q_meanstar				6.925	4.471	3.701
				(5.753)	(5.673)	(5.911)
lag4q_meanstar					-14.60**	-15.37**
					(6.059)	(6.331)
lag5q_meanstar						-4.325
						(5.977)
cum_meanstar	146.5**	121.6*	83.52	62.87	111.8	127.6
	(63.11)	(70.00)	(71.37)	(71.69)	(79.99)	(81.94)
totalquarterreviews	16.44***	16.43***	16.40***	16.39***	16.39***	16.40***
	(6.193)	(6.189)	(6.185)	(6.179)	(6.184)	(6.184)
cum_totalquarterreviews	0.298**	0.300**	0.302**	0.303**	0.302**	0.302**
	(0.136)	(0.135)	(0.135)	(0.134)	(0.134)	(0.134)
y_lag1	0.215***	0.216***	0.215***	0.215***	0.215***	0.215***
	(0.0556)	(0.0555)	(0.0555)	(0.0556)	(0.0555)	(0.0555)
Constant	3,390***	3,440***	3,515***	3,554***	3,465***	3,438***
	(356.8)	(367.4)	(363.3)	(368.5)	(378.8)	(375.2)
Observations	27,485	27,485	27,485	27,485	27,485	27,485
R-squared	0.761	0.761	0.761	0.761	0.761	0.761
City FE	YES	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

*** p<0.01, ** p<0.05, * p<0.1

Another threat to identification could be the existence of confounding variables affecting online consumer reviews and restaurant wages. The first potential confounding variable is the quality of food and service that may meet or exceed consumers' expectations and result in higher consumer ratings. Restaurants that provide better food and service to consumers may be able to set higher prices, achieving higher wages for their workers. Ideally, I could use a variable that indicates the quality of food and service in a restaurant as an instrument variable to address confounding issues. Although there is no such information for each restaurant in this sample, a restaurant fixed effect could control the time-invariant aspect of this.

Another potential confounding variable to consider is the size of a restaurant. Larger restaurants, capable of accommodating more customers, might generate a higher volume of online consumer reviews. Concurrently, these large establishments may also leverage economies of scale, driving up their revenue, which in turn allows them to offer higher wages to their employees. This concern is mitigated by the implementation of the restaurant fixed effect, which remains constant throughout the duration of this study.

Finally, a restaurant's reputation could influence both online consumer reviews and the wages it offers. Famous restaurants may attract more consumers and generate more reviews or higher star ratings. These restaurants are likely to pay higher wages to their workers because of their success. This dataset doesn't explicitly denote whether a restaurant is well-known or a so-called 'internet celebrity' restaurant. However, I do have information indicating whether a restaurant belongs to a chain or is independently operated, allowing me to discern the heterogeneous effects of online consumer reviews on wages across these two types of restaurants. Once again, the restaurant fixed effect could provide control for this potential confounder.

This paper aims to establish the causal relationship between online consumer reviews and wages within the restaurant industry. Previous research has demonstrated, using a range of methodologies, that online consumer reviews cause an increase in demand for restaurant meals. However, due to the absence of revenue data for the restaurants in this sample, I cannot establish a direct causal link between increased demand for restaurant meals and subsequent wage increases within these establishments. Despite this limitation, if I can establish a causal relationship between online consumer reviews and restaurant wages, I can confirm that online consumer reviews cause demand for restaurant meals to increase, which in turn causes restaurant wages to increase.

2.7 Heterogeneous Effects

In this section, I begin by adding an interaction term that combines reviews with a chain restaurant dummy variable. This approach allows me to examine the influence of mean star rating, cumulative mean star rating, quarterly reviews, and cumulative quarterly reviews on the mean quarterly wages across both chain and independent restaurants. Next, I segment the total sample into three subgroups: independent restaurants, chain restaurants, and major chain restaurants. This division is intended to investigate potential variations in the relationships between the variables of interest and the mean quarterly wage across these groups.

To explore whether there is an interaction effect among variables of interest on mean quarterly wages, I introduce interaction terms of variables of interest to the fixed effects model for the whole sample. Finally, I further divide the total sample into the previously mentioned categories to examine whether group differences exist. This final step aims to assess potential variations in the relationships between the variables of interest and the mean quarterly wages across the different restaurant categories.

A body of research suggests that online consumer reviews affect chain and independent restaurants differently because a chain-affiliated restaurant could convey quality information through its reputation, while independent restaurants rely more heavily on online consumer reviews (Luca, 2011; Makofske, 2020). More specifically, chain restaurants share a unified brand name, similar menus, joint advertising programs, and a consistent food sourcing management system. These similarities cause consumers to have more knowledge about chain-affiliated restaurants than independent restaurants (Luca, 2011).

There is no consensus on the definition of chain or independent restaurants based on the number of their locations (Liang & Andris, 2022). In Delaware, chain restaurants are defined as "sit-down restaurant, fast-food outlet, café, coffee shop, convenience store, deli, bakery, cookie counter, or ice cream shop, that does business under the same trade name as used by ten (10) or more other establishments doing business in Delaware or nationally" (Delaware SENATE BILL NO. 81, 2009). In New York, a restaurant is classified as a chain if it does business under the same trademark with 15 or more locations (New York S2532 | TrackBill, 2021.). While the definition of chain restaurants varies from state to state, I have not found an official definition of chain restaurants in Colorado.

In this study, I define an independent restaurant as a food establishment in Colorado that operates in only one location under one trademark and is not listed as part of a restaurant chain in the United States on Wikipedia (Wikipedia, 2023). If there are two or more restaurant locations under one trademark in Colorado or a restaurant only has one location in Colorado but is in the restaurant chain list in the United States, I consider it a restaurant chain. In instances where ten or more restaurant locations operate under one trademark within Colorado, I classify it as a major restaurant chain.

To explore whether the effect of online consumer reviews on mean quarterly wages varies between chain and independent restaurants, I add interaction terms of chain and other independent variables to the fixed effects models. The findings in Table 2.5 are consistent with the previous baseline models —cumulative mean star rating (*cum_meanstar*), quarterly reviews (*totalquarterreviews*), and cumulative quarterly reviews (*cum_totalquarterreviews*) drive the growth of mean quarterly wages. Across the four models with an interaction term, only the interaction term of quarterly reviews and chain (*inter_qreviews_chain*) is statistically significant. This finding suggests that the influence of quarterly reviews on mean quarterly wages differs between chain and independent restaurants, with a more pronounced effect observed in independent restaurants.

Table 2.5: Estimation Results from Fixed Effects Models with interaction terms

	(1)	(2)	(3)	(4)	(5)
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
meanstar	-2.913	-8.897	-2.955	-2.998	-3.009
	(4.185)	(7.611)	(4.192)	(4.163)	(4.105)
cum_meanstar	39.70***	38.79***	31.92	39.20***	39.51***
	(12.16)	(12.44)	(21.63)	(12.25)	(12.16)
totalquarterreviews	16.24***	16.25***	16.26***	18.30***	16.14***
	(5.940)	(5.943)	(5.938)	(6.359)	(6.015)
cum_totalquarterreviews	0.559***	0.558***	0.558***	0.529***	0.601***
	(0.104)	(0.103)	(0.103)	(0.102)	(0.0966)
y_lag1	0.301***	0.301***	0.301***	0.301***	0.301***
	(0.0362)	(0.0362)	(0.0362)	(0.0361)	(0.0361)
inter_meanstar_chain		10.45			
		(7.302)			
inter_cmeanstar_chain			12.69		
			(23.95)		
inter_qreviews_chain				-8.801***	
				(3.186)	
inter_creviews_chain					-0.215
					(0.200)
Constant	3,026***	3,035***	3,035***	3,033***	3,030***
	(158.7)	(162.3)	(159.3)	(160.8)	(157.1)
Observations	63,230	63,230	63,230	63,230	63,230
R-squared	0.766	0.766	0.766	0.766	0.766
City FE	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

*** p<0.01, ** p<0.05, * p<0.1

Further, I study how the effect of online reviews differs across independent, chain, and major chain restaurants. Tables 2.6, 2.7, and 2.8 display the estimated results from fixed effects models for independent, chain, and major chain restaurants, respectively.

As shown in Table 2.6, the cumulative mean star rating (*cum_meanstar*), total quarterly reviews (*totalquarterreviews*), and cumulative quarterly reviews (*cum_totalquarterreviews*) increase employees' wages in independent restaurants. Interestingly, the mean star rating estimates are not significant across the five different specifications for independent restaurants. This indicates that customer demand isn't influenced by the star rating in the current quarter; instead, it's driven by ratings from previous quarters. One possible explanation is that consumers do not view the current rating as a robust indicator of restaurant quality for independent establishments. If an independent restaurant has performed well in prior quarters, consumers may still consider it a worthwhile dining experience regardless of its current rating.

Table 2.6: Estimation Results from Fixed Effects Models - Independent Restaurants

Variable	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
meanstar	-3.740	-11.21	-3.852		-11.25
	(7.932)	(8.212)	(7.903)		(8.197)
cum_meanstar		52.93**		35.51	52.44**
		(22.83)		(23.18)	(22.99)
totalquarterreviews	19.99***	19.85***	17.83***	17.73***	17.70***
	(5.622)	(5.592)	(6.340)	(6.329)	(6.310)
cum_totalquarterreviews			0.312**	0.310**	0.311**
			(0.125)	(0.125)	(0.125)
y_lag1	0.287***	0.287***	0.285***	0.285***	0.285***
	(0.0497)	(0.0498)	(0.0487)	(0.0487)	(0.0487)
Constant	3,332***	3,163***	3,334***	3,188***	3,167***
	(218.2)	(224.3)	(213.6)	(228.3)	(219.3)
Observations	34,394	34,394	34,394	34,394	34,394
R-squared	0.758	0.758	0.758	0.759	0.759
City FE	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

*** p<0.01, ** p<0.05, * p<0.1

Table 2.7 showcases the estimates of the fixed effects models employed for analyzing chain restaurants, utilizing various specifications—from Model 1 to Model 5. As I move across these models, it is consistently observed that the estimates for the number of quarterly reviews (*totalquarterreviews*), cumulative reviews (*cum_totalquarterreviews*), and the lagged mean quarterly wage (*y_lag1*) are all positive. More importantly, these estimates are statistically significant, implying a robust positive correlation with the mean quarterly wages in chain restaurants. These findings align well with the earlier work of Cui et al. (2012), which demonstrated that an increase in review volume could positively influence the demand for products, particularly in the early stage post-launch.

In the case of Model 5, it is worth noting that the coefficient of the *meanstar* is not statistically significant at the 5% level. However, its positive sign aligns with the results found in Model 1. This could be indicative of the fact that consumers attach importance to the mean star rating for chain restaurants within a given quarter. Chain restaurants, after all, are known for maintaining a certain level of standards, whether in terms of food quality, service, or management.

Table 2.7: Estimation Results from Fixed Effects Models - Chain Restaurants

Variable	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
meanstar	5.157*	1.431	4.160		1.339
	(2.890)	(3.476)	(2.934)		(3.500)
cum_meanstar		22.25		19.01	16.89
		(15.76)		(13.27)	(15.62)
totalquarterreviews	15.37***	15.30***	10.88**	10.87**	10.87**
	(5.541)	(5.572)	(4.244)	(4.260)	(4.259)
cum_totalquarterreviews			0.862**	0.856**	0.856**
			(0.334)	(0.336)	(0.336)
y_lag1	0.334***	0.334***	0.329***	0.329***	0.329***
	(0.0140)	(0.0139)	(0.0145)	(0.0144)	(0.0144)
Constant	2,923***	2,864***	2,932***	2,885***	2,887***
	(58.20)	(81.21)	(57.16)	(76.28)	(79.32)
Observations	28,836	28,836	28,836	28,836	28,836
R-squared	0.774	0.774	0.775	0.775	0.775
City FE	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

*** p<0.01, ** p<0.05, * p<0.1

Table 2.8 presents the estimated results of the fixed effects model specifically focused on major chain restaurants, defined as food establishments operating more than ten locations under a single trademark in Colorado. Across the five distinct models, a common pattern emerges: both cumulative mean star ratings and the number of quarterly reviews appear to contribute to an increase in restaurant mean quarterly wages. This relationship holds despite some coefficients not reaching statistical significance in certain specifications. I draw this conclusion as long as the directions of the estimated effect are the same. Interestingly, a comparison of the coefficients of quarterly reviews (*totalquarterreviews*) between chain and independent restaurants reveals that the latter exhibits larger coefficients. This observation aligns well with these findings, as presented in Table 2.5, suggesting that review impact might be more pronounced for independent establishments compared to their chain counterparts.

Table 2.8: Estimation Results from Fixed Effects Models - Major Chain Restaurants

	(1)	(2)	(3)	(4)	(5)
Variable	Model 1	Model 2	Model 3	Model 4	Model 5
meanstar	-1.027	-6.470	-1.004		-6.421
	(4.107)	(4.917)	(4.077)		(4.888)
cum_meanstar		30.04*		19.58	29.90*
		(15.33)		(12.85)	(15.29)
totalquarterreviews	12.00	12.00*	11.02	11.06	11.05
	(7.253)	(7.200)	(8.473)	(8.482)	(8.461)
cum_totalquarterreviews			0.474	0.469	0.461
			(0.788)	(0.805)	(0.805)
y_lag1	0.328***	0.327***	0.327***	0.327***	0.327***
	(0.0190)	(0.0190)	(0.0191)	(0.0191)	(0.0191)
Constant	2,845***	2,773***	2,840***	2,781***	2,768***
	(80.95)	(93.94)	(79.18)	(88.99)	(92.21)
Observations	15,125	15,125	15,125	15,125	15,125
R-squared	0.740	0.740	0.740	0.740	0.740
City FE	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

*** p<0.01, ** p<0.05, * p<0.1

Table 2.9 showcases the results from the fixed effects model, using data from the entire sample. I clustered standard errors at the city level to account for potential correlation within specific groups. Model 1, the baseline model, did not include any interaction terms. According to the results from this model, I found a positive association between three variables - cumulative mean star rating, number of quarterly reviews, and cumulative quarterly reviews - and the mean quarterly wages. This indicates that as these factors increase, so do the mean quarterly wages.

In Model 2, I expanded this analysis to incorporate an interaction term between the mean star rating and the number of quarterly reviews. Interestingly, the coefficient for this interaction term was not statistically significant, suggesting that the relationship between the mean star rating and the number of quarterly reviews does not significantly influence the mean quarterly wages. Similarly to Model 2, the coefficient of the interaction term between the cumulative mean star rating and quarterly reviews does not achieve statistical significance in Model 5.

Table 2.9: Estimated Fixed Effects Models with Interaction Terms -Whole Sample

Variable	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
meanstar	-2.913	-7.608	-9.433**	-2.855	-2.768
	(4.185)	(5.089)	(3.887)	(4.170)	(4.197)
cum_meanstar	39.70***	40.81***	44.88***	36.16***	34.63***
	(12.16)	(12.00)	(12.41)	(12.51)	(13.21)
totalquarterreviews	16.24***	8.215	16.25***	16.33***	5.983
	(5.940)	(7.556)	(5.896)	(5.863)	(13.11)
cum_totalquarterreviews	0.559***	0.541***	-0.253	-1.213**	0.550***
	(0.104)	(0.0983)	(0.409)	(0.580)	(0.100)
y_lag1	0.301***	0.301***	0.301***	0.301***	0.301***
	(0.0362)	(0.0362)	(0.0362)	(0.0362)	(0.0362)
inter_meanstar_quarterreviews		2.059			
		(1.302)			
inter_meanstar_cumreviews			0.198**		
			(0.0971)		
inter_cummeanstar_cumreviews				0.442***	
				(0.158)	
inter_cummeanstar_quarterreviews					2.633
					(2.532)
Constant	3,026***	3,042***	3,035***	3,047***	3,046***
	(158.7)	(159.7)	(157.6)	(160.5)	(154.2)
Observations	63,230	63,230	63,230	63,230	63,230
R-squared	0.766	0.766	0.766	0.766	0.766
City FE	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

*** p<0.01, ** p<0.05, * p<0.1

Models 3 and 4 in Table 2.9 demonstrate comparable patterns in their results. In Model 3, the coefficients of the primary variables, namely mean star rating and cumulative quarterly reviews, are both positive and significant. Additionally, the interaction term in Model 3 also shows a positive and significant coefficient. These findings indicate that as cumulative quarterly reviews increase, the impact of the mean star rating on mean quarterly wages becomes stronger. Similarly, as the mean star rating rises, the effect of cumulative quarterly reviews on mean quarterly wages becomes more pronounced. The results in Model 4 exhibit a similar pattern, albeit with a different interaction term. In both cases, the main variables have positive coefficients, while the interaction term remains positive as well, reflecting a consistent pattern observed in Models 2 and 3.

To investigate the impact of the interaction terms among the variables of interest on mean quarterly wages across distinct restaurant categories, I perform regression analyses using high-dimensional fixed effects models on independent, chain, and major chain restaurants. Table 2.10 displays the estimated fixed effects model results for independent restaurants, with standard errors clustered at the city level to ensure robustness.

Table 2.10: Estimated Fixed Effects Models with Interaction Terms - Independent Restaurants

Variable	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
meanstar	-11.25	-10.62	-21.27**	-11.12	-11.40
	(8.197)	(7.936)	(8.525)	(8.190)	(8.372)
cum_meanstar	52.44**	52.32**	59.30***	48.11**	57.09**
	(22.99)	(22.76)	(22.18)	(23.69)	(27.08)
totalquarterreviews	17.70***	18.59*	17.72***	17.80***	25.47
	(6.310)	(11.08)	(6.246)	(6.215)	(23.01)
cum_totalquarterreviews	0.311**	0.312***	-0.653	-1.379*	0.313**
	(0.125)	(0.117)	(0.480)	(0.727)	(0.120)
y_lag1	0.285***	0.285***	0.285***	0.284***	0.285***
	(0.0487)	(0.0487)	(0.0487)	(0.0487)	(0.0485)
inter_meanstar_quarterreviews		-0.224			
		(1.761)			
inter_meanstar_cumreviews			0.233*		
			(0.130)		
inter_cummeanstar_cumreviews				0.419**	
				(0.188)	
inter_cummeanstar_quarterreviews					-1.956
					(4.465)
Constant	3,167***	3,164***	3,184***	3,190***	3,148***
	(219.3)	(216.5)	(219.4)	(221.8)	(198.6)
Observations	34,394	34,394	34,394	34,394	34,394
R-squared	0.759	0.759	0.759	0.759	0.759
City FE	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

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

For independent restaurants, two main factors drive the mean quarterly wages: the mean star rating received over time and the number of quarterly reviews. The coefficient of the lagged mean quarterly wage, significant at 0.285, suggests that the past wage values moderately influence current ones, even after controlling for time-invariant characteristics. Moreover, the significant interaction term between the mean star rating and cumulative reviews indicates that as the number of reviews increases, the impact of the current mean star rating on the mean quarterly wage becomes more pronounced, and vice versa. Additionally, an interaction effect exists between the mean cumulative star rating and cumulative reviews, even after adjusting for unobserved time-invariant characteristics. These findings highlight the importance of both the quality and quantity of reviews in influencing the mean wages of independent restaurants.

Table 2.11 provides the estimated fixed effects models incorporating interaction terms between key variables for chain restaurants. These results vary slightly from the ones detailed for independent restaurants in Table 2.9. From this data, I can assert that cumulative quarterly reviews and lagged mean quarterly wages have a positive correlation with mean quarterly wages. Yet, I lack sufficient evidence to conclusively establish the impact of the mean star rating, cumulative mean star rating, and total quarterly reviews on the mean quarterly wages of chain restaurants. A noteworthy observation from Model 2 is the positive and statistically significant coefficient of the interaction term, indicating an interaction effect between the mean star rating and quarterly reviews, even after adjusting for unobserved time-invariant characteristics. Similarly, the impact of the cumulative mean star rating on mean quarterly wages appears to depend on cumulative reviews, with all other variables held constant and vice versa. It is also important to highlight that Model 5 presents the largest interaction effect among the four different model specifications.

Table 2.11: Estimated Fixed Effects Models with Interaction Terms - Chain Restaurants

Variable	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
meanstar	1.339	-9.259*	-2.754	1.356	1.668
	(3.500)	(5.130)	(4.285)	(3.476)	(3.451)
cum_meanstar	16.89	19.52	20.52	14.06	2.499
	(15.62)	(15.47)	(16.53)	(15.88)	(19.44)
totalquarterreviews	10.87**	-9.496*	10.87**	10.96**	-22.29*
	(4.259)	(5.314)	(4.258)	(4.298)	(13.05)
cum_totalquarterreviews	0.856**	0.797**	0.214	-1.058	0.792**
	(0.336)	(0.318)	(0.724)	(1.054)	(0.308)
y_lag1	0.329***	0.328***	0.329***	0.329***	0.329***
	(0.0144)	(0.0145)	(0.0144)	(0.0144)	(0.0144)
inter_meanstar_quarterreviews		5.627***			
		(1.857)			
inter_meanstar_cumreviews			0.162		
			(0.125)		
inter_cummeanstar_cumreviews				0.488*	
				(0.271)	
inter_cummeanstar_quarterreviews					9.076**
					(4.365)
Constant	2,887***	2,921***	2,892***	2,905***	2,943***
	(79.32)	(82.42)	(79.01)	(78.76)	(89.02)
Observations	28,836	28,836	28,836	28,836	28,836
R-squared	0.775	0.775	0.775	0.775	0.775
City FE	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

*** p<0.01, ** p<0.05, * p<0.1

Table 2.12 presents the estimated fixed effects models, which explore the interactions between the key variables for major chain restaurants. In examining the five models, I notice an inconsistency in how the mean star rating and total reviews in a quarter impact mean quarterly wages. However, there is a notable consistency in the effects of the cumulative mean star rating and cumulative quarterly reviews on the mean quarterly wages. Across all five models, their influence remains positive.

Table 2.12: Estimated Fixed Effects Models with Interaction Terms - Major Chain Restaurants

Variable	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
meanstar	-6.421	-19.43***	-9.149*	-6.631	-6.184
	(4.888)	(6.602)	(5.348)	(4.898)	(4.872)
cum_meanstar	29.90*	32.36**	32.29**	39.62**	20.12
	(15.29)	(15.13)	(15.17)	(18.19)	(15.01)
totalquarterreviews	11.05	-12.64	11.11	10.30	-10.60
	(8.461)	(15.09)	(8.507)	(7.843)	(19.38)
cum_totalquarterreviews	0.461	0.529	0.0293	6.712*	0.444
	(0.805)	(0.830)	(1.072)	(3.942)	(0.815)
y_lag1	0.327***	0.326***	0.327***	0.326***	0.327***
	(0.0191)	(0.0193)	(0.0192)	(0.0192)	(0.0192)
inter_meanstar_quarterreviews		8.477***			
		(3.017)			
inter_meanstar_cumreviews			0.153		
			(0.278)		
inter_cummeanstar_cumreviews				-1.942	
				(1.367)	
inter_cummeanstar_quarterreviews					7.164
					(4.902)
Constant	2,768***	2,797***	2,768***	2,738***	2,797***
	(92.21)	(98.98)	(92.63)	(99.53)	(97.70)
Observations	15,125	15,125	15,125	15,125	15,125
R-squared	0.740	0.740	0.740	0.740	0.740
City FE	YES	YES	YES	YES	YES
Restaurant FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES

Robust standard errors in parentheses, clustered at the city level

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

A critical observation in Model 4 is that the coefficient of interaction terms is negative. This implies a diminishing effect of the cumulative mean star rating on the mean quarterly wages as the number of cumulative reviews increases. Furthermore, I find a significant coefficient for the lagged mean quarterly wage at 0.327. This indicates that the wages from the preceding quarter significantly affect the current quarter's mean wages. Such insights can aid in forecasting future wage trends.

2.8 Conclusion

Previous studies have confirmed that online consumer reviews impact demand and revenues (Luca, 2011; Anderson and Magruder, 2012). This research uncovers further effects of online consumer reviews. I discover that cumulative mean star rating, the number of quarterly reviews, and cumulative reviews all positively influence mean quarterly wages in the entire sample. The effect of the cumulative mean star rating on mean quarterly wages is more substantial than that of the mean star rating. This may be because cumulative mean star rating provides more comprehensive information on the historical quality of the restaurant. A high cumulative mean star rating indicates a consistent provision of high-quality products or services, which would influence consumer demand more than the mean star rating in the current quarter. Additionally, the impact of the number of quarterly reviews on mean quarterly wages is greater than that of cumulative quarterly reviews. This may suggest that the wages in the current quarter are more relevant to the number of reviews in the current quarter, which is a good proxy for the dined consumers in the restaurant.

I observe that the current quarter mean star rating affects mean quarterly wages in chain restaurants while the cumulative mean star rating influences quarterly wages for independent restaurants. This demonstrates that consumers pay attention to the short-term performance of chain restaurants while paying attention to the long-term performance of independent restaurants. The restaurant industry is competitive and dynamic, with constant operation and consumer preferences changes. This dynamic aspect is more resembled in independent restaurants than in chain restaurants because chain restaurants share standard operations and management. Consumers value a track record of consistent, high-level performance more than in chain restaurants to infer whether an independent restaurant would provide good food and service.

I also observe that the relationships within the mean star rating, cumulative mean star rating, the number of quarterly reviews, and cumulative quarterly reviews on mean quarterly wages differ for independent and chain restaurants. The interaction term effect is less pronounced in independent restaurants than in chain restaurants. This could be attributed to the fact that chain restaurants can achieve economies of scale, which helps cut costs and increase profits. In this way, chain restaurants could secure more wages for their employees from the increased demand from a higher cumulative mean star rating and a greater number of reviews.

These findings indicate that at the beginning of a restaurant's opening, the demand for meals at the chain and major chain restaurants is primarily driven by reviews, particularly when there is a scarcity of information regarding the quality of competing establishments in the market. This result aligns with Friberg and Grönqvist (2012), who find that expert reviews matter the most for newly introduced wines. Similar to wine, a restaurant meal is an experience good for most people. Reviews from the current quarter and previous quarters communicate the quality of restaurant meals to consumers, helping them make informed dining choices.

These results do not align with Luca (2011), where the impact of consumer reviews on restaurant demand is primarily attributed to independent restaurants. In this study, the mean star rating, the number of quarterly reviews, and cumulative quarterly reviews increase the mean quarterly wages for both independent and chain restaurants. Given that chain restaurants already convey information about their food quality, these results demonstrate that consumers use online reviews for both independent and chain restaurants.

This study suggests that chain restaurants, as a result of demand shifts prompted by online consumer reviews, tend to generate higher wages for their employees compared to independent restaurants. For independent restaurants to be able to thrive in the competitive restaurant industry, the key takeaway from this study is the imperative of delivering consistently superior products and services. In contrast, chain restaurants only need to focus on the food and service quality in the current quarter because this matters the most to consumers. In addition, they should also concentrate on standardized operations that can minimize average costs and boost overall profits. For policymakers, it is important to provide more policy support to independent restaurants that can invigorate the restaurant industry by offering more diversified restaurant meals to consumers.

This research investigates the impact of online reviews and various aspects of these reviews on restaurant wages. It presents evidence that reviews influence the demand for restaurant meals and, consequently, restaurant wages. This finding holds significance for restaurant managers, who typically concentrate on restaurant operations rather than monitoring online consumer reviews. Moreover, the results are important for consumers, as they reveal that reviews from fellow consumers assist others in making dining decisions, which can alter the demand for restaurants.

References

Anderson, M., & Magruder, J. (2012). Learning from the Crowd: Regression Discontinuity Estimates of the Effects of an Online Review Database. *The Economic Journal*, *122*(563), 957–989. https://doi.org/10.1111/j.1468-0297.2012.02512.x

Cai, Hongbin, Yuyu Chen, and Hanming Fang. (2009). Observational Learning: Evidence from a Randomized Natural Field Experiment. *American Economic Review*, 99 (3): 864-82.

Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, *43*(3), 345–354. https://doi.org/10.1509/jmkr.43.3.345

Colorado Department of Labor and Employment. (2021). Minimum Wage Retrieved February 23, 2021, from https://cdle.colorado.gov/wage-and-hour-law/minimum-wage

Colorado Restaurant Association | Industry Statistics. (2021). Retrieved February 23, 2021, from https://corestaurant.org/newsroom/industry-statistics

Cui, G., Lui, H.-K., & Guo, X. (2012). The Effect of Online Consumer Reviews on New Product Sales. *International Journal of Electronic Commerce*, *17*, 39–58. https://doi.org/10.2307/41739503

Department of Labor. (2023). History of Federal Minimum Wage Rates Under the Fair Labor Standards Act, 1938—2009. Retrieved June 28, 2023, from http://www.dol.gov/agencies/whd/minimum-wage/history/chart

Duflo, E., & Saez, E. (2003). The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *The Quarterly journal of economics*, *118*(3), 815-842.

Friberg, Richard, and Erik Grönqvist. (2012). Do Expert Reviews Affect the Demand for Wine? *American Economic Journal: Applied Economics*, 4 (1): 193-211.

Hilger, J., Rafert, G., & Villas-Boas, S. (2011). Expert Opinion and the Demand for Experience Goods: An Experimental Approach in the Retail Wine Market. *Review of Economics and Statistics*, *93*(4), 1289–1296. https://doi.org/10.1162/REST_a_00117

Liang, X., & Andris, C. (2022). Measuring McCities: Landscapes of chain and independent restaurants in the United States. *Environment and Planning B: Urban Analytics and City Science*, *49*(2), 585–602. https://doi.org/10.1177/23998083211014896

Luca, M. (2011). Reviews, Reputation, and Revenue: The Case of Yelp.Com. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1928601

Makofske, M. P. (2020). The Effect of Information Salience on Product Quality: Louisville Restaurant Hygiene and Yelp.com*. *The Journal of Industrial Economics*, *68*(1), 52–92. https://doi.org/10.1111/joie.12214

Moretti, E. (2011). Social Learning and Peer Effects in Consumption: Evidence from Movie Sales. *The Review of Economic Studies*, *78*(1), 356–393. https://doi.org/10.1093/restud/rdq014

Nelson, P. (1970). Information and Consumer Behavior. *Journal of Political Economy*, 78(2), 311–329. https://doi.org/10.1086/259630

SENATE BILL NO. 81, DELAWARE STATE SENATE 145th GENERAL ASSEMBLY. (2009). https://legis.delaware.gov/json/BillDetail/GetHtmlDocument?fileAttachmentId=38576

New York S2532 | *TrackBill*. (2021). https://trackbill.com/bill/new-york-senate-bill-2532-requires-chain-restaurants-to-label-menu-items-that-have-a-high-content-of-sodium/1992586/

Reinstein, D. A., & Snyder, C. M. (2005). The Influence of Expert Reviews on Consumer Demand for Experience Goods: A Case Study of Movie Critics*. *The Journal of Industrial Economics*, *53*(1), 27–51. https://doi.org/10.1111/j.0022-1821.2005.00244.x

Wikipedia 2023. List of restaurant chains in the United States List of restaurant chains in the United States - Wikipedia

3 A CHOICE EXPERIMENT APPROACH TO INFORM POLICY FOR INCREASING CONSERVATION PRACTICE ADOPTION

3.1 Introduction

The rate of adoption of conservation practices is relatively low in certain parts of the US. For example, the percentage of no-till or strip-till in the Fruitful Rim, the agricultural region covering parts of California, Arizona, Idaho, Washingon, and Oregon, is only 19%, which is far behind other parts of the US (Wade et al., 2015). If these sluggish adoption rates for conservation practices continue in agricultural sectors, both agricultural producers and consumers could face adverse effects such as deteriorating soil health and increasing greenhouse gas emissions (Wade et al., 2015). Soil erosion is estimated to cost US $44.39 billion from losing productivity on cropland and adding sediments and nitrogen to bodies of water (Halopka, 2017). This presents an urgent challenge for policymakers to design efficient conservation practice programs that most agricultural producers would want to adopt.

Conservation practice programs aim to support agricultural producers in preserving soil health, maintaining water and air quality, protecting wildlife habitat, and reducing greenhouse gas emissions (USDA, 2019). For example, the Environmental Quality Incentives Program (EQIP) uses monetary incentives to encourage agricultural producers to adopt conservation practices like nutrient management, conservation tillage, and cover crops on their cropland (USDA, 2019).

Recent research has extensively studied factors that have affected agricultural producers' adoption of conservation practices. Researchers analyzed how conservation program characteristics (Wilson 1997; Breetz et al., 2005; Ruto and Garrod, 2009; Hoag et al., 2012), farm/ranch characteristics (Featherstone and Goodwin, 1993; Wilson, 1997; Prokopy et al., 2008; Hoag et al., 2012), and agricultural producer characteristics (Breetz et al., 2005; Ahnström et al., 2009; Loomis and Gascogne, 2018) affect conservation practice adoption. Program characteristics like payment level (Cooper, 2003; Hoag et al., 2012), participation time (Cooper, 2003; Hoag et al., 2012), trust in program specialist (Breetz et al., 2005), continuous payment and opt-out option (Wilson, 1997) are also determining factors that affect agricultural producers' decision to participate in conservation practice. Farm/ranch characteristics, including landowner status (Featherstone and Goodwin, 1993; Wilson, 1997) and corporate agricultural producer status (Featherstone and Goodwin, 1993), significantly affect agricultural producers' likeliness to participate in conservation practice. Demographics (Breetz et al., 2005; Ahnström et al., 2009; Loomis and Gascogne, 2018) of agricultural producers, such as age, income, and education level, influence their willingness to participate in conservation practice.

While previous research has focused on the characteristics of conservation programs, agricultural producers, and their land, few studies have treated conservation practice as a conservation good and suggested how to design a program that agricultural producers are willing to adopt. This study aims to fill this gap by identifying two characteristics and studying their efficacy in promoting the adoption of conservation practices. The two characteristics are cost-share and technical assistance, because policy makers can change the price of conservation practice through cost-sharing and can improve agricultural producers' skills in conservation practice through technical support.

This paper aims to study the effect of farmers' perceived cost of conservation practices on their adoption preferences to provide insights for designing conservation practice policies. Specifically, I focus on the impact of perceived cost on the adoption of soil testing, conservation tillage, filter and buffer strips, as well as the use of slow and controlled release fertilizer.

To achieve this objective, I design a choice experiment to ask agricultural producers to choose between options with different levels of cost-sharing and technical assistance. In addition, I account for both agricultural producers' average belief and their subjective beliefs on the costs of conservation practice. I conducted this choice experiment using mailed and Qualtrics surveys.

The contribution of this paper is twofold. First, I utilize Lancaster's (1966) consumer theory and treat conservation programs as consumer goods. Lancaster (1966) points out that a good provides utility to the consumer through the sum of the utility of its characteristics. Similarly, a conservation program delivers utility to an agricultural producer through the sum of the utility of its characteristics. For example, the characteristics in Ruto and Garrod’s (2009) study are "minimum contract length,” "flexibility over what areas of the farm are entered into the scheme,” "flexibility over undertaking some of the measures required under the scheme,” "average paperwork time," and "additional payment per hectare under the scheme." They use these characteristics to study farmers' preferences to help design better agri-environment programs. Using this perspective allows me to employ advances in consumer economics to study the willingness of agricultural producers to adopt conservation practices. It also points attention to the design of the conservation good as a way to increase adoption, as opposed to many studies that look at the characteristics of a fixed population of farmers and farms.

Second, this study accounts for agricultural producers' heterogeneity by eliciting their beliefs on the perceived cost of conservation practice. Cost is usually treated as a given that is not controlled by the producer, but producers base decisions on what they perceive. Lusk et al. (2014) have shown that incorporating beliefs in consumer willingness to pay in studies is important because failing to do so can lead to biased empirical estimates and a misunderstanding of research findings. They also show that researchers understand consumer behavior better after carefully considering consumers' beliefs about the studied subject. Similarly, this methodology attempts to better interpret agricultural producers’ choices by accounting for their beliefs on the costs of conservation practices. This allows me to study agricultural producers' preferences to design a conservation practice program that can encourage them to join.

3.2 Literature review

Various studies have examined how the characteristics of conservation practice programs affect farmers' participation in conservation practices. Financial incentives, technical support, and contract length are prominent factors that affect farmers' participation in these programs. Cooper (2003) and Copper and Signorello (2008) found that payment incentives are needed to promote conservation plan adoption among farmers. Recent works focus on how different designs of payment incentives affect farmers' decisions on conservation plan adoption. For example, Palm-Foster et al. (2017) used experimental auctions to study how different financial incentives affect farmers' willingness to adopt voluntary phosphorus abatement in agricultural watersheds. Moreover, Osmond et al. (2015) found that funding resources, technical support, and education on watersheds increase farmers' undertaking of nutrient management. Ruto and Garrod (2009) used choice experiment data from 10 case study areas across the EU and found that farmers prefer short contracts with more payments. Abdulai et al. (2014) and Juutinen et al. (2014) calculated the optimal contract length for biodiversity and soil conservation practices, respectively.

The demographics of farmers also affect their uptake of conservation practices. An array of research examined how farmers' landownership affects their conservation practices (Featherstone and Goodwin, 1993; Wilson, 1997; Soule et al., 2000; Sklenicka et al., 2015). Although the regions and conservation practices of studies differ, the evidence is clear that landowners are more likely to implement conservation practices than land lessees. Another array of related research has found mixed effects of farmers' age on their decisions to adopt conservation practices. For example, in the review conducted by Prokopy et al. (2019), which covers quantitative studies that span 35 years in the US, age negatively affects conservation practice 25 times and positively nine times.

Similarly, farmers' implementation costs of conservation practice play a role in their future participation. Organic farmers have already been using practices that resulted in a lower implementation cost to adopt conservation practices. A body of literature (Best, 2010; Gabel et al., 2018; Mack et al., 2020) finds that organic farmers are more likely to adopt conservation practices. Other factors associated with implementation costs, such as distance to plot and plot steepness, are related to conservation practice enrollment. For instance, Lakner et al. (2020) find that German farmers with more plots located further away from their residences are less likely to participate in German agri-environmental programs. Similarly, Huber et al. (2021) identified a positive relationship between plot steepness and enrollment rates for Swiss farmers participating in a Swiss Alpine agri-environmental program.

Farmers' environmental attitudes may affect their decisions to participate in conservation practices. Giovanopoulou et al. (2011) measure farmers' environmental attitudes with questions like whether farmers' primary focus is preserving the environment. Yeboah et al. (2015) use five-point Likert-type scale questions to measure farmers' attitudes toward filter strips and general environmental attitudes and use these attitudinal variables to estimate farmers' enrollment in the Conservation Reserve Enhancement Program. Both studies find a positive relationship between positive environmental attitudes and conservation practice participation.

A growing body of literature increasingly emphasizes the importance of separating beliefs from preferences in food choices. Lusk et al. (2014) used three sets of choice experimental data to demonstrate that subjective beliefs should be accounted for when interpreting results from choice data. Pappalardo and Lusk (2016) extend this study to consumer choices of functional foods. Malone and Lusk (2018) further extend this analysis to consumers' purchasing process of beer brands.

The interaction of the literature that studies the factors that affect conservation practice adoption and the literature focusing on distinguishing beliefs from preferences in consumer food choices generates a hypothesis that lays the foundation of this study. That is, how producers' beliefs on implementing conservation practice affect their conservation practice choices. This paper tests this hypothesis by eliciting farmers' beliefs about the cost of implementing conservation practices and letting farmers choose from a choice experiment that includes several conservation practice scenarios.

3.3 Experimental Design

After summarizing information from the literature, I discussed conservation practices with agricultural experts at Colorado State University. I then determined that the following four conservation practices would best suit this study: soil testing, conservation tillage, filter and buffer strips, and slow and controlled release fertilizer.

I identified the two attributes of these practices and their relative levels. I select cost share and technical support as relevant attributes because they are common practices in conservation programs. Cost-sharing is a continuous dimension with set points at 0%, 25%, and 50%. For example, a 25% cost share means that the program pays 25% of the cost of the conservation practice. As the allocation of cost sharing is linear, I coded this variable in its actual value.

Conversely, technical support is categorial, so I set it at three different gradual levels. The low level merely provides agricultural producers with a website where they can find information on the given conservation practice and print out the instructions on how to implement it. The medium level of support includes the low-level attribute and adds a 1-800 helpline where agricultural producers can seek relevant guidance when encountering problems implementing the conservation practice. Finally, the high level of support includes the attribute of the medium level plus personalized, on-farm support from a government agricultural specialist. I coded these three levels of technical support with three dummy variables because their relationship is not linear. Table 3.1 shows the attributes and attribute levels used in the study.

Table 3.1: Attributes and Attribute levels

Attributes	Levels	Coded using:
Cost share	No cost share	actual values
	25% cost share	
	50% cost share	
Technical support	Website and printed instructions	dummy variables
	Website, printed instructions, and 1-800 helpline	
	Website, printed instructions, 1-800 helpline, and on-farm support	

With attributes information at hand, I then designed choice experiments following (Louviere et al., 2000; Aizaki and Nishimura, 2008). In R software, I first use the AlgDesign Package to create a full factorial design that contains 3*3=9 rows. Then, I create a fractional factorial design and make copies of this design. Finally, I generate choice sets by randomly selecting them without replacement. Table 3.2 below provides an example of the choice set used in the mailed and online survey. For each conservation practice, there are six choice sets. I use the same six-choice sets for conservation tillage, soil testing, filter and buffer strips, and slow and controlled release fertilizer.

Table 3.2: An example of choice set in the survey

If you were able to choose, which of the following three options would you choose?		
A 50% cost share and Website and printed instructions	No cost sharing and Website, printed instructions, and 1-800 helpline	Would not adopt

In the survey on conservation practices, I directly solicit respondents' subjective beliefs about the costs involved. Specifically, in the conservation tillage survey, I introduce the research purpose —what it would take to encourage more farmers to practice conservation tillage in their operations. Then I briefly talk about the levels of cost-sharing and technical assistance. Following this, I request respondents to provide their estimates regarding the cost impact of conservation tillage on their operations. The question is phrased as follows: "Let's start by telling us what you estimate conservation tillage adds (subtracts) to your costs on a per-acre basis: $_______ per acre."

3.4 Conceptual Framework

The choice experiment method is built upon Lancaster's (1966) theory that a consumer good provides utility through the sum of the utility of its characteristics. The choice experiment is also derived from McFadden's (1974) random utility theory. This theory proposes that the traditional utility function is composed of two parts: one systematic part that depends on the attributes of the alternative and another random part that is stochastic (Ubilava and Foster, 2009). Following McFadden (1974) and Train (1998), the utility of individual n choosing the choice alternative i in the choice set t is

$$U_{nit} = V_{nit} + \varepsilon_{nit} \tag{3.1}$$

where V_{nit} is the systematic part of the utility. ε_{nit} is the stochastic part of the utility and is identically and independently distributed.

The mixed logit model differs from the standard logit model, which assumes respondents have homogeneous preferences. While the parameter estimates for all variables in the standard logit model are fixed, the effect of a random variable on utility in the mixed logit model can be parsed into a mean effect and a standard deviation effect on utility (Colombo et al., 2005). Because there exists a mean effect on utility and a standard deviation effect for a random variable (Train 1998), I can write the deterministic part of utility as

$$V_{nit} = \beta' x_{nit} = b_n f_{nit} + (\overline{\mu_n} + \theta_n')r_{nit} \tag{3.2}$$

where x_{nit} are observable variables, and β represent the corresponding coefficients. b_n represents the vector parameters for fixed variables f_{nit}, $\overline{\mu_n}$ represents the mean effects of random variables r_{nit}. $\theta_n$represents the deviation effects of random variables r_{nit}.

In the baseline model, I specify the utility function as

$$U_{nit} = \beta_1 subsidy_{nit} + \beta_2' medsupport_{nit} + \beta_3' highsupport_{nit} + \beta_4 optout_{nit} + \varepsilon_{nit} \tag{3.3}$$

In equation (3.3), the construction of the *subsidy* variable is achieved through two methods: first, by multiplying the *costshare* with the average cost belief, and second, by multiplying the *costshare* with the individual cost belief. *Costshare* is a variable that has three categories: 0%, 25%, and 50%. The variable *subsidy* is treated as a fixed variable because I cannot assume the parameters for the subsidy to be normally distributed, while in reality, the coefficient of subsidy is usually positive (see Ubilava and Foster, 2009). Here, β_1 represents the coefficient for the *subsidy* variable.

β_2 , β_3 are normally distributed parameters for random variables *medsupport* and *highsupport*. The variable *medsupport* is 1 if the technical support is “Website, printed instructions, and 1-800 helpline” and 0 otherwise. The variable *highsupport* is 1 if the technical support is “Website, printed instructions, 1-800 helpline, and on-farm support”, and 0 otherwise. The variable *optout* takes the value of 1 for the opt-out alternative and 0 otherwise. It serves as the constant in the model and captures the utility difference between opting in one of the conservation practice alternatives and opting out. ε_{nit} is the unobserved part of individual n utility.

Further, I can write the utility functions as:

$$U_{nit} = \beta_1 belief_{avg} * costshare_{nit} + \beta_2' medsupport_{nit} + \beta_3' highsupport_{nit} + \beta_4 optout_{nit} + \varepsilon_{nit} \tag{3.4}$$

$$U_{nit} = \beta_1 belief_n * costshare_{nit} + \beta_2' medsupport_{nit} + \beta_3' highsupport_{nit} + \beta_4 optout_{nit} + \varepsilon_{nit} \tag{3.5}$$

A respondent would choose alternative i if and only if $U_{ni} > U_{nj}$ for any $j \neq i$. Following Train (1998, 2003), the probability of individual n choosing alternative i in the choice set t in a conditional logit model framework conditional on β_n is:

$$L_{nit}(\beta_n) = \frac{e^{\beta' x_{nit}}}{\sum_j e^{\beta' x_{njt}}} \tag{3.6}$$

Because β_n is not observable, the mixed logit choice probability is the integral of $L_{nit}(\beta_n)$ over all values of β (Train, 1998). The choice probability for individual n chooses alternative i from the choice set t is:

$$P_{nit} = \int \left(\frac{e^{\beta' x_{nit}}}{\sum_j e^{\beta' x_{njt}}} \right) f(\beta|\theta^*) d\beta \tag{3.7}$$

where β is the distribution of parameters from β_n. θ^* represents the parameters of the random variable across the respondents, such as mean and standard deviation (Train, 1998). $f(.)$ is the density function for observable variables. For fixed variables, $f(.) = 1$.

In addition, willingness to accept (WTA) for an attribute is calculated as the marginal rate of substitution between the coefficient of that attribute and the coefficient of the price attribute. Thus, the function of WTA for medium and high support can be written as:

$$WTA_m = \frac{MU_m}{MU_{subsidy}} = \frac{\beta_m}{\beta_{subsidy}} \tag{3.8}$$

$$WTA_h = \frac{MU_h}{MU_{subsidy}} = \frac{\beta_k}{\beta_{subsidy}} \tag{3.9}$$

where WTA_m represents the monetary value respondents would like to accept for the medium level of support for a conservation practice. β_m is the estimated coefficient for the medium-level support attribute and β_h is the estimated coefficient for the high-level support attribute.

3.5 Data

The data collection took place from February 2020 to April 2021, during which I sent several rounds of surveys via mail to agricultural producers in Colorado. However, as the COVID-19 pandemic took hold in the United States just as I began this process, I also provided an online option via Qualtrics survey links. These were emailed to the same set of agricultural producers in Colorado as a precautionary measure, acknowledging possible apprehensions towards handling physical mail due to the virus. Ultimately, I was able to gather a total of 555 raw responses. Given that this survey was conducted without real-time guidance on completion, a significant number of responses were incomplete. Only 152 respondents answered all the choice set questions in full. To be more specific, I received 41 complete responses for conservation tillage, 39 for soil testing, 37 for buffer strips, and 35 for controlled release fertilizer. Unfortunately, due to confusion among agricultural producers regarding the belief question, I was required to exclude additional responses.

The first column of Table 3.3 shows the descriptive statistics for respondents who answered conservation tillage choice questions. The mean age of these respondents is 57.47 years, with an average farming experience of 37.61 years. Moreover, the data indicates that 60.53% of respondents have a spouse contributing additional income outside of farm work. Farmers with a college degree or higher account for 85.37% of respondents, suggesting that the majority of the sample is highly educated. When looking at annual sales, 34.14% of farmers report less than \$100,000, while 53.67% have sales exceeding \$100,000. Note that the percentage of farm sales does not sum to 100 because of missing values.

Table 3.3: Sample Demographics (Unit: year/percent)

Demographic	Categorical levels	CT	ST	BS	CR
Age	None	57.47	61.76	61.40	60.55
Farming Years	None	37.61	42.54	37.68	39.21
Spouse Off-Farm Job	YES	60.53	43.24	40.00	37.50
Education	No High School	7.32	2.63	5.41	5.71
	High School	7.32	15.79	16.22	8.57
	College or Technical	56.10	55.26	56.76	51.43
	Graduate or Professional	29.27	26.32	21.62	34.29
Farm Sales	under \$50,000	17.07	18.42	10.81	11.43
	\$50,000- \$99,999	17.07	18.42	5.41	14.29
	\$100,000 - \$249,999	19.51	26.32	21.62	14.29
	\$250,000 - \$499,999	12.20	7.89	24.32	17.14
	\$500,000 - \$1,000,000	12.20	5.26	16.22	20.00
	over \$1,000,000	9.76	18.42	13.51	17.14
Number of Respondents	None	41	39	37	35

Note: CT - conservation tillage, ST - soil testing, BS - buffer strips, CR - controlled-release fertilizer

Table 3.3 shows the descriptive statistics for respondents who answered choice experiment questions. The table represents the four conservation practices, conservation tillage, soil testing, buffer strips, and controlled release fertilizer, represented by CT, ST, BS, and CR, respectively. The conservation tillage sample sees the youngest mean age (57.47) of the farmers, while the rest of the samples have an average age above 60 years old. The mean farming years of the respondents from the four samples range from 37 to 43 years, indicating a large proportion of the respondents have rich experience in farming and agriculture.

In terms of whether respondents' spouses have off-farm jobs, respondents from the conservation tillage sample lead with 60.53%, while the rest of the samples have less than 50%. The distribution of educational achievement levels across all four samples displays a similar pattern, with the majority holding either a college or technical degree, or a graduate or professional qualification. Lastly, the distribution of farm sales among the four samples exhibits notable variation.

Table 3.4: Summary Statistics of Cost Belief Variables – Participant belief about practice cost ($/ac)

Cost Belief Variable	Observations	Mean	Std. Dev.	Min	Max
Conservation Tillage	30	31.72	46.70	0	200
Soil Testing	33	47.56	96.56	0	500
Buffer Strips	36	95.58	140.99	0	500
Controlled Release	30	25.72	43.04	0	200

Table 3.4 presents the summary statistics for cost belief variables across four samples: conservation tillage, soil testing, buffer strips, and controlled release fertilizers. The buffer strips sample holds the highest cost belief value at $95.58, followed by the soil testing sample at $47.56, the conservation tillage sample at $31.72, and finally, the controlled release fertilizer sample with the lowest value at $25.72. The heterogeneity in cost belief is the largest in the buffer strip sample and smallest in the controlled release fertilizer sample. Interestingly, I find zero values in each conservation practice, indicating a significant hesitancy towards the adoption of these conservation strategies.

3.6 Empirical results

Because each respondent in this sample has to answer six choice questions, I utilize a random parameter model (also known as the mixed logit model) to account for the repeated nature of data and heterogeneous preferences. I first estimate the baseline model (Model 1) assuming beliefs are homogeneous across respondents by multiplying the average cost belief with cost share while accounting for belief heterogeneity by multiplying individual *belief* and *costshare* in Model 2.

All the mixed logit model results are estimated in NLOGIT 6.0, a statistical software specialized in analyzing discrete choice experiment data. I estimate all the models with the simulated maximum likelihood method using 90 Halton draws and then gradually increase to 200 Halton draws. I select the number of Halton draws based on two criteria: 1) all model specifications need to converge; 2) the estimates of the selected number of Halton draws need to be consistent when the number of Halton draws increases. In the two models, the random variables are assumed to follow normal distributions.

Table 3.5: Conservation Tillage - Mixed logit model estimates

Attribute	Model 1	Model 2
Medium Support	1.013	1.345**
	(0.801)	(0.599)
High Support	1.398	2.567*
	(2.079)	(1.313)
Avg. Belief X Costshare	0.093**	
	(0.044)	
Optout	0.364	-0.583*
	(0.758)	(0.299)
Belief X Costshare		0.057***
		(0.017)
Standard Deviation Effects		
Std. Dev. Medium Support	1.464***	2.199***
	(0.555)	(0.671)
Std. Dev. High Support	4.335***	6.246***
	(1.457)	(2.019)
Observations	168	168
Log-Likelihood	-145.185	-139.598
AIC	302.400	291.200

Note: *** p <0.01, ** p <0.05, * p <0.1.
Estimated using 90 Halton Draws

Table 3.5 reports the mixed logit model estimates in the two different specifications. Standard errors are reported in parenthesis. Following Zemo and Termansen (2018), I convert the cost share percentage by multiplying it with an average cost belief in the conservation practice sample to derive monetary estimates in Model 1. In Model 2, I account for heterogeneous cost beliefs by multiplying the individual cost beliefs with the cost share variable.

In Model 1, the estimated coefficient for the *subsidy* variable, which is *Avg. Belief X Costshare,* is positive and significant. This implies that if the program subsidizes farmers with the amount equal to their average cost belief, a high cost share encourages farmers to participate in the conservation tillage practice. Though not significant, a medium and high level of support increase a respondent's likelihood of using conservation tillage. The coefficient of *Optout* is positive, which means that farmers' utilities derived from opting out are higher than any of the other two alternatives.

Model 2 presents a different scenario when I account for individual cost belief by multiplying it with cost share. The coefficients associated with medium and high support levels are both positive and statistically significant. This suggests that a medium or high level of support significantly bolsters farmers' propensity to engage in conservation tillage practices. The coefficient of the *subsidy* variable, produced by multiplying individual cost belief and cost share, demonstrates that subsidies structured around an individual's beliefs enhance the perceived utility for farmers to implement conservation measures on their land, therefore improving farmers' adoption of conservation tillage.

In these two models, the parameters corresponding to medium and high support are treated as random, while the *subsidy* variable and the *Optout* variable are considered fixed. This approach primarily stems from the convenience it provides in deriving the estimates for willingness to accept, compared to when the parameters for the subsidy variable are randomized (Ubilava and Foster 2009). Notably, the standard deviation effects for random variables medium and high support are larger when I account for individual beliefs.

Table 3.6: Soil Testing - Mixed logit model estimates

Attribute	Model 1	Model 2
Medium Support	0.523	-0.435
	(0.506)	(0.305)
High Support	-1.817	-3.549*
	(2.337)	(2.128)
Avg. Belief X Costshare	0.075***	
	(0.028)	
Optout	1.006	-0.787***
	(0.726)	(0.233)
Belief X Costshare		0.003
		(0.004)
Standard	Deviation Effects	
Std. Dev. Medium Support	1.099***	0.860***
	(0.390)	(0.331)
Std. Dev. High Support	7.153**	6.448**
	(3.050)	(2.644)
Observations	192	192
Log-Likelihood	-163.609	-167.353
AIC	339.200	346.700

Note: *** p <0.01, ** p <0.05, * p <0.1.
Estimated using 90 Halton Draws.

Table 3.6 contains the estimated results in two different mixed logit model specifications for the soil testing sample. These specifications echo those utilized in the conservation tillage sample. In contrast to the results from Model 1 in Table 3.5, the coefficient for high level of support in this context is negative. This suggests that a high level of support is not a preferred choice for farmers; instead, they exhibit a preference for a medium level of support, as indicated by its positive coefficient. The subsidy variable has a coefficient of 0.072 and is statistically significant, implying that subsidies are the main driver motivating farmers to test their soils. A positive *Optout* coefficient in Model 1 indicates that respondents gain more utility from opting out.

However, the results from Model 2 are stunningly different from Model 1. The negative coefficients of medium and high support indicate that farmers prefer just the website and printed instructions, demonstrating a lack of interest in either helpline or on-farm support. The coefficient for the *subsidy* variable is positive but not significant. The negative and significant coefficient of *Optout* shows that farmers are more inclined to choose one of the two alternatives offering monetary and technical support rather than opting out.

Table 3.7: Buffer Strips - Mixed logit model estimates

Attribute	Model 1	Model 2
Medium Support	-0.349	-0.866***
	(0.404)	(0.269)
High Support	-3.021*	-4.072**
	(1.704)	(1.622)
Avg. Belief X Costshare	0.022*	
	(0.013)	
Optout	0.125	-0.980***
	(0.687)	(0.261)
Belief X Costshare		0.001
		(0.003)
Standard Deviation Effects		
Std. Dev. Medium Support	0.467	0.354
	(0.433)	(0.449)
Std. Dev. High Support	4.027**	4.024**
	(1.630)	(1.602)
Observations	174	174
Log-Likelihood	-153.262	-154.817
AIC	318.500	321.600

Note: *** p <0.01, ** p <0.05, * p <0.1.
Estimated using 90 Halton Draws.

Table 3.7 outlines the mixed logit model estimates for two distinct specifications within the buffer strips sample. In Model 1, only the *subsidy* variable is statistically significant, signifying that an increase in the subsidy - calculated as the product of average cost belief and cost share - heightens respondents' propensity to adopt buffer strips. Contrarily, the negative signs of the coefficients for medium and high levels of support in Model 1 suggest that respondents derive the most utility from a low level of support.

In Model 2, the negative signs of medium and high levels of support align with the results from Model 1. The negative sign on the *Optout* variable suggests that farmers are more inclined to select an alternative that doesn't involve opting out. The coefficient of the *subsidy* variable is positive, albeit smaller than its counterpart in Model 1. Interestingly, the heterogeneity in the distributions of medium and high levels of support shows a slight decrease after accounting for heterogeneity in cost beliefs.

Table 3.8: Controlled Release Fertilizer - Mixed logit model estimates

Attribute	Model 1	Model 2
Medium Support	0.315	-0.271
	(0.367)	(0.273)
High Support	0.669	-0.507
	(0.644)	(0.454)
Avg. Belief X Costshare	0.129***	
	(0.042)	
Optout	0.335	-0.980***
	(0.605)	(0.283)
Belief X Costshare		0.042**
		(0.017)
Standard Deviation Effects		
Std. Dev. Medium Support	0.615*	0.567*
	(0.318)	(0.289)
Std. Dev. High Support	1.560***	1.684***
	(0.484)	(0.501)
Observations	174	174
Log-Likelihood	-162.475	-162.481
AIC	337.000	337.000

Note: *** p <0.01, ** p <0.05, * p <0.1.
Estimated using 90 Halton Draws.

Table 3.8 presents the mixed logit model outcomes for two distinct specifications relating to the controlled release fertilizer sample. Across both specifications, a consistent finding emerges: subsidies enhance farmers' propensity to adopt controlled release fertilizer on their farms. While Model 1 indicates that farmers favor medium and high levels of support over a low level of support, Model 2 suggests that any level of support is satisfactory for farmers. In Model 1, the positive coefficient for the opt-out choice suggests that farmers derive more utility from selecting the opt-out option. However, this narrative changes in Model 2, where farmers benefit more when they choose an alternative other than opting out.

Table 3.9: WTA payments in mixed logit model 1 using Krinsky and Robb Method (unit: dollars)

Attribute	Conservation Tillage	Soil Testing	Buffer Strips	Controlled Fertilizer
Medium_support	-10.92	-6.94	15.54	-2.43
	[-153.28, 131.44]	[-28.54, 14.66]	[-341.47, 372.55]	[-10.17, 5.30]
High_support	-15.08	24.13	134.70	-5.18
	[-589.12, 558.95]	[-122.66, 170.92]	[-1927.62, 2197.02]	[-17.61, 7.25]

Table 3.10: WTA payments in mixed logit model 2 using Krinsky and Robb Method (unit: dollars)

Attribute	Conservation Tillage	Soil Testing	Buffer Strips	Controlled Fertilizer
Medium_support	-23.76	143.11	1463.54	6.44
	[-45.07, -2.45]	[-18434.40, 18720.63]	[-15791.31, 18718.39]	[-154.01, 166.88]
High_support	-45.36	1168.70	6879.39	12.05
	[-92.21, 1.48]	[-77422.24, 79759.63]	[-74200.94, 87959.71]	[-759.84, 783.93]

I use Krinsky and Robb (1986) method to obtain the willingness to accept the (WTA) estimate and confidence interval instead of the Delta method. While the two methods produce the same mean WTA, the confidence interval for WTA from the two methods differs. The Krinsky-Robb method is more appropriate because it relaxes the symmetrically distributed WTA assumption (Hole, 2007).

The Krinsky and Robb method is calculated using Monte Carlo simulation (Hensher et al., 2015). It includes the following steps as instructed in Hensher et al. (2015). To estimate the willingness to accept from the mixed logit model, I first obtain parameter estimates and a variance-covariance matrix using the specified utility function. I then use the Cholesky decomposition from the variance-covariance to randomly draw a vector x from a standard normal distribution and construct vector Z by adding the product of the multiplier of the Cholesky decomposition and the vector x to the parameter vector. I repeat this process 90 times to generate a distribution of WTA estimates, which I sort from minimum to maximum value. Finally, I obtain the 95 percent confidence interval by eliminating the top 2.5 percent and bottom 2.5 percent of the values. These steps are calculated using NLOGIT 6.0.

Table 3.9 presents the mean willingness to accept estimates for respondents in the four conservation practice samples. On average, farmers in the buffer strips sample are willing to accept \$15.54 per acre for the medium level of support and \$134.70 per acre for the high level of support. However, the estimates for other samples are mostly negative, indicating that respondents are willing to pay a certain amount of money to adopt conservation practices.

Table 3.10 includes the mean willingness to accept estimates for respondents after accounting for individual cost beliefs in the four samples. Compared with Table 3.9, only WTA estimates for conservation tillage sample respondents are negative, suggesting respondents are willing to pay to adopt conservation tillage. Buffer strips respondents see the highest WTA for medium and high levels of support, followed by soil testing and controlled fertilizer samples.

3.7 Discussion and Conclusion

The objective of this paper is to explore the impact of farmers' perceived cost on conservation practices on their adoption preferences. I design a choice experiment to study farmers' preference heterogeneity in cost share and technical support in four conservation practices—conservation tillage, soil testing, buffer strips, and slow and controlled fertilizers.

Results show that farmers are more willing to adopt the four conservation practices in the study if provided with a higher cost share. This result is not surprising because it is consistent with a number of studies that point out cost as a main obstacle for farmers to participate in conservation practices (Cooper, 2003; Hoag et al., 2012). In the post-pandemic days, when prices start to increase, the cost is anticipated to play an even larger role in moderating farmers' likelihood of joining conservation programs. This suggests that policymakers need to pay more attention to designing cost-related program characteristics.

Technical support is important for conservation tillage respondents. While it is natural to consider technical support as necessary when promoting conservation programs, the result from the soil testing, buffer strip, and controlled release fertilizer sample suggests that other aspects other than technical support are worth exploring.

I observe significant differences in farmers' preferences across the four conservation practices. These differences are mainly due to their perceived cost heterogeneity, which implies that one size for all conservation practice policy may not be suitable for everyone. This piece of evidence suggests that accounting for perceived cost heterogeneity benefits farmers.

This study provides insight into how conservation practice policy could be designed, emphasizing the necessity of considering farmer diversity and preference heterogeneity. Given the challenge of altering demographic characteristics, tailoring policy attributes to achieve higher adoption rates is a more feasible approach.

However, this study has certain limitations. The response rate is low, and the sample size is small due to the COVID-19 pandemic. Consequently, caution is required when interpreting and generalizing the results. To address these limitations, future research should strive to gather a more comprehensive dataset, ensuring more robust and reliable conclusions.

References

Abdulai, A., & Goetz, R. (2014). Time-Related Characteristics of Tenancy Contracts and Investment in Soil Conservation Practices. *Environmental and Resource Economics*, *59*(1), 87–109. https://doi.org/10.1007/s10640-013-9719-y

Ahnström, J., Höckert, J., Bergeå, H. L., Francis, C. A., Skelton, P., & Hallgren, L. (2009). Farmers and nature conservation: What is known about attitudes, context factors and actions affecting conservation? *Renewable Agriculture and Food Systems*, *24*(1), 38–47. https://doi.org/10.1017/S1742170508002391

Aizaki, H., & Nishimura, K. (2008). Design and Analysis of Choice Experiments Using R: A Brief Introduction. *Agricultural Information Research*, *17*(2), 86–94. https://doi.org/10.3173/air.17.86

Best, H. (2010) Environmental concern and the adoption of organic agriculture. *Society and Natural Resources*, 23, 451–468.

Breetz, H. L., Fisher-v, K., Jacobs, H., & Schary, C. (2005). Trust and Communication: Mechanisms for Increasing Farmers' Participation in Water Quality Trading. *Land Economics*, 170–190.

Colombo, S., Hanley, N., & Calatrava-Requena, J. (2005). Designing Policy for Reducing the Off-farm Effects of Soil Erosion Using Choice Experiments. *Journal of Agricultural Economics*, *56*(1), 81–95. https://doi.org/10.1111/j.1477-9552.2005.tb00123.x

Cooper, J.C. (2003). A joint framework for analysis of agri-environmental payment programs. *American Journal of Agricultural Economics*, 85(4), 976-87.

Cooper, J. C., & Signorello, G. (2008). Farmer Premiums for the Voluntary Adoption of Conservation Plans. *Journal of Environmental Planning and Management*, *51*(1), 1–14. https://doi.org/10.1080/09640560701712234

Featherstone, A. M., & Goodwin, B. K. (1993). Factors influencing a farmer's decision to invest in long-term conservation improvements. *Land Economics*, 69(1),67-81.

Gabel, V.M., Home, R., Stolze, M., Pfiffner, L., Birrer, S. & Köpke, U. (2018) Motivations for swiss lowland farmers to conserve biodiversity: Identifying factors to predict proportions of implemented ecological compensation areas. *Journal of Rural Studies*, 62, 68–76.

Giovanopoulou, E., Nastis, S.A. & Papanagiotou, E. (2011) Modeling farmer participation in agri-environmental nitrate pollution reducing schemes. *Ecological Economics*, 70, 2175–2180.

Halopka Richard. (2017). The high cost of soil erosion. *Farm Progress* https://www.farmprogress.com/soil-health/high-cost-soil-erosion

Hensher, D. A., Rose, J. M., & Greene, W. H. (2015). *Applied Choice Analysis* (2nd ed.). Cambridge University Press. https://doi.org/10.1017/CBO9781316136232

Hoag, D. L., Luloff, A. E., & Osmond, D. L. (2012). *Socioeconomic Analysis: National Institute of Food and Agriculture–Conservation Effects Assessment Project*. 18.

Hole, A. R. (2007). A comparison of approaches to estimating confidence intervals for willingness to pay measures. *Health Economics*, *16*(8), 827–840. https://doi.org/10.1002/hec.1197

Huber, R., Zabel, A., Schleiffer, M., Vroege, W., Brändle, J.M. & Finger, R. (2021) Conservation Costs Drive Enrolment in Agglomeration Bonus Scheme. *Ecological Economics*, 186, 107064.

Juutinen, A., Ollikainen, M., Mönkkönen, M., Reunanen, P., Tikkanen, O.-P., & Kouki, J. (2014). Optimal contract length for biodiversity conservation under conservation budget constraint. *Forest Policy and Economics*, *47*, 14–24. https://doi.org/10.1016/j.forpol.2013.11.008

Krinsky, I., Robb, A.L. (1986). On Approximating the Statistical Properties of Elasticities. *The Review of Economics and Statistics* 68(4), 715-719.

Lakner, S., Zinngrebe, Y. & Koemle, D. (2020) Combining management plans and payment schemes for targeted grassland conservation within the Habitats Directive in Saxony, Eastern Germany. *Land Use Policy*, 97, 104642.

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy*, *74*(2), 132–157.

Loomis, J., & Gascoigne, W. (2018). Understanding Agricultural Producers' Willingness to Undertake Self-Monitoring of Environmental Outcomes: Results of a Choice Experiment with Colorado Agricultural Producers. *Journal of Natural Resource Policy Research*, *8*(1–2), 22.

Louviere, J. J., Hensher, D. A., Swait, J. D., & Adamowicz, W. (2000). *Stated Choice Methods: Analysis and Applications* (1st ed.). Cambridge University Press. https://doi.org/10.1017/CBO9780511753831

Lusk, J., Schroeder, T., & Tonsor, G. (2014). Distinguishing beliefs from preferences in food choice. *European Review of Agricultural Economics*, *41*, 627–655. https://doi.org/10.1093/erae/jbt035

Malone, T., & Lusk, J. L. (2018). An instrumental variable approach to distinguishing perceptions from preferences for beer brands. *Managerial and Decision Economics*, *39*(4), 403–417. https://doi.org/10.1002/mde.2913

Mack, G., Ritzel, C. & Jan, P. (2020) Determinants for the implementation of action-, result-and multi-actor-oriented agri-environment schemes in Switzerland. *Ecological Economics*, 176, 106715.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In: Zarembka, P. (ed.), *Frontier in Econometrics*. Academic Press, New York.

Osmond, D. L., Hoag, D. L. K., Luloff, A. E., Meals, D. W., & Neas, K. (2015). Farmers' Use of Nutrient Management: Lessons from Watershed Case Studies. *Journal of Environmental Quality*, *44*(2), 382–390. https://doi.org/10.2134/jeq2014.02.0091

Palm-Forster, L. H., Swinton, S. M., & Shupp, R. S. (2017). Farmer preferences for conservation incentives that promote voluntary phosphorus abatement in agricultural watersheds. *Journal of Soil and Water Conservation*, *72*(5), 493–505. https://doi.org/10.2489/jswc.72.5.493

Pappalardo, G., & Lusk, J. L. (2016). The role of beliefs in purchasing process of functional foods. *Food Quality and Preference*, *53*, 151–158. https://doi.org/10.1016/j.foodqual.2016.06.009

Prokopy, L. S; Floress, K; Klotthor-Weinkauf, D; Baumgart-Getz, A. (2008) Determinants of agricultural best management practice adoption: Evidence from the literature. *Journal of Soil and Water Conservation*, 63,5; ProQuest pg.300.

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S. P., Eanes, F. R., Gao, Y., Gramig, B. M., Ranjan, P., & Singh, A. S. (2019). Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. *Journal of Soil and Water Conservation*, *74*(5), 520–534. https://doi.org/10.2489/jswc.74.5.520

Ruto, E., & Garrod, G. (2009). Investigating farmers' preferences for the design of agri-environment schemes: A choice experiment approach. *Journal of Environmental Planning and Management*, *52*(5), 631–647. https://doi.org/10.1080/09640560902958172

Sklenicka, P., Molnarova, K. J., Salek, M., Simova, P., Vlasak, J., Sekac, P., & Janovska, V. (2015). Owner or tenant: Who adopts better soil conservation practices? *Land Use Policy*, *47*, 253–261. https://doi.org/10.1016/j.landusepol.2015.04.017

Soule, M. J., Tegene, A., & Wiebe, K. D. (2000). Land Tenure and the Adoption of Conservation Practices. *American Journal of Agricultural Economics*, *82*(4), 993–1005. https://doi.org/10.1111/0002-9092.00097

Train, K. E. (1998). Recreation Demand Models with Taste Differences over People. *Land Economics*, *74*(2), 230–239. https://doi.org/10.2307/3147053

Wade, T., Claasen, R., & Wallander, S. (2015). Conservation-Practice Adoption Rates Vary Widely by Crop and Region. *U.S. Department of Agriculture, Economic Research Service*, *EIB-147*.

Ubilava, D., & Foster, K. (2009). Quality certification vs. product traceability: Consumer preferences for informational attributes of pork in Georgia. *Food Policy*, *34*(3), 305–310. https://doi.org/10.1016/j.foodpol.2009.02.002

USDA ERS - Conservation Programs. (2019). Retrieved May 12, 2022, from https://www.ers.usda.gov/topics/natural-resources-environment/conservation-programs/

Wilson, G. A. (1997). Factors Influencing Farmer Participation in the Environmentally Sensitive Areas Scheme. *Journal of Environmental Management*, *50*, 67–93. https://doi.org/10.1006/jema.1996.0095

Yeboah, F.K., Lupi, F. & Kaplowitz, M.D. (2015) Agricultural landowners' willingness to participate in a filter strip program for watershed protection. Land Use Policy, 49, 75–85.

Zemo, K. H., & Termansen, M. (2018). Farmers' willingness to participate in collective biogas investment: A discrete choice experiment study. *Resource and Energy Economics*, *52*, 87–101. https://doi.org/10.1016/j.reseneeco.2017.12.001